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New Frontiers in Brain-Computer Interfaces

Edited by Nawaz Mohamudally,
Manish Putteeraj and Seyyed Abed Hosseini

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Meet the editors

Dr Nawaz Mohamudally graduated in telecommunications from the University of Science and Technology of Lille I in France and is currently an Associate Professor and former Chairman of the Research Degrees Committee at the University of Technology, Mauritius where he has also been the Head of the School of Software Engineering and Business Informatics and the School of Innovative Technologies and Engineering. He was the chairman of the Internet Management Committee, an advisory unit to the Mauritian authority from 2010 to 2014. His core research areas are mobile and pervasive computing and data science. Dr Mohamudally was awarded the "Best Professor in Industrial Systems Engineering" Africa Education Leadership Award in 2015. His contributions in Brain Computer Interface are in the field of "thought-to-text".

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Contents

Preface

Researchers have, for a long time, tried to, and are today highly successful at, demystifying the human brain through brain signals. In the field of computer science, early attempts were more algorithmic, focused on artificial neural networks in order to solve complex software engineering problems. The advent of possibilities offered by Brain Computer Interface (BCI) has opened up avenues for a plethora of research and development projects. The latest published advancement in the field is the famous "thought-to-text" application, whereby an individual thought could be transformed into textual information. One may guess the potentials for such an advancement in the medicine field.

The mathematical armada to allow digital processing of brain signals, coupled with progression in sensors and electrodes has prompted innovative products on the market. Capturing raw data from one's brain with in-built software for analysis could be produced as a bundle on the market at affordable prices. With more computational power and visualisation techniques, future generations of neuroscientists will undoubtedly be in a more knowledgeable situation, probably the notion of computer interface with the brain might look more natural that it is now.

Nonetheless, BCI remains an ocean to be explored and this book aims at capturing the ongoing activities globally. The chapters comprise deep research with solid mathematical foundations supplemented with experimental results. Moreover readers will find extensive lists of references pertaining to BCI and original contributions of the chapters from the authors. The manuscript is therefore a trusted primary source of information on BCI.

New Frontiers in Brain Computer Interfaces is a compilation of recent achievements ranging from optical technologies, mental task-based BCI, speech enhancement, brain dynamics, and brain-computer modelling. Authors across the globe have formulated the chapters to be accessible to students, lecturers, and researchers, as well as readers passionate about the topic. This book aims to disseminate the latest findings and research work in BCI. There is potential for future research for PhD students as well as food for thought about the next generation of BCI technologies.

We wish to thank all the authors for their efforts and good will to make this book project possible. Without their contributions, recent knowledge about BCI would remain hidden. A vote of thanks to the IntechOpen Author Service Manager Ms Dolores Kuzelj, the technical board, and the commissioning editor. Providing open access to knowledge is undoubtedly a noble cause.

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Chapter 1

Introductory Chapter: The "DNA Model" of Neurosciences and Computer Systems

Manish Putteeraj and Shah Nawaz Ali Mohamudally

1. Introduction

The technological advances made in the recent years have moved beyond the conventional research and design framework that used to singularly focus on the problem at hand and resolve it using the best approaches within the same field. Current systems cater for crossbridges across disciplines for problem solving, a process that creates multiple opportunities toward sustainable and cutting-edge innovations. This design of inter-relationality across dimensions has served well in developing modern techniques such as the use of brain waves to understand human behavior and similar methods toward the introduction of machine learning (ML) stemming from artificial intelligence (AI). This has also led to popular and insightful methods such as brain-computer interfaces (BCI) that are gaining much momentum especially in modern medicine. However, much needs to be done in the field of neurosciences and computer systems to exploit the resources for their respective progression and nurture the existing ecosystem. This chapter will provide an overview of a "DNA model" concept that shows the relative interdependence of brain sciences and computer systems in research and unravel unexplored areas for probing scientists.

1.1 Demystifying the brain

The mammalian brain is arguably the most complex organ of the body with over 100 billion neurons and glial cells which are scattered across the lobes for specific functionality. The neurodevelopmental process consists of multiple stages inclusive of migration, differentiation, maturation, synaptogenesis, pruning, and myelination, among others, which provides the basis for brain development [1]. ML and AI are overlap constructs of neurocomputing, which can be said to be founded on principles of synaptogenesis, a biological process forming the basis of signal integration at the brain level. In a simplistic overview, the mammalian body responds to the environment based on a sensory input integrated at the neuronal level to trigger relevant output. This is also reflected in the decision-making process, whereby the brain computes multiple scenarios for comparison based on the information crunched in different brain regions before initiating the action for the desired value [2]. Applicability of this type of brain process has been made possible using modern noninvasive neuroimaging techniques such as electroencephalograms (EEGs), enabling the visualization and patterning of brain activity for informed decisions. Research by Poli et al. (2013) [3] has effectively demonstrated such applicability of BCI using a neuroscience platform to enhance noncommunicative group-based decision-making process solely relying on a supervised machine learning platform

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with an eightfold cross-validation approach. Although at its embryonic stage, this type of research can be further exploited in real-life settings to exclude the argumentative part and enhance the time taken for group-based decision-making process.

1.2 Brain circuitry and artificial neural networks

Brain circuitry, i.e., the synaptic connectivity of individual neurons in one or more brain regions, is vital for a potent signal integration and transmission. Similarly, neuronal interaction via synapses has been shown to be critical for memory recall and learning, via recurrent signal generation at those areas of connectivity [4, 5]. This is comparable to the application of artificial neural networks (ANN) using soft fuzzy logic to compute multiple variables to autonomously generate tailored solutions based on adaptability as well as the governance of signal transmission via weights, a feature that to a certain extent mimics synaptic plasticity of the brain in memory formation and recall [6, 7]. The crossbridge between neurosciences and computer systems is not only reflected in the setup/programming of the system but also in terms of information being fed in real time for fine-tuning of outputs. Using supervised learning algorithms such as the back-propagation algorithms is necessary to assist in marginalizing the gap between expected and actual outputs and render information parsing and predictability meaningful [8]. This physiologic term is termed as the feedback loop system enabling the correction of any deviations at the systemic level or normalization of neuromodulatory signals via neurofeedback systems. Interestingly, ANN also recreates a biological neuronal system via its “artificial firing at the nodal region” akin to action potentials, mediating passage of signals downstream for a source to its effector region [9]. This feedforwarding process in artificial setups also termed as axonal saltatory conduction in the brain has been found to be efficient for the speed of signal transmission.

1.3 Analysis of brain signals

Innovations have demonstrated the use of brain waves and software recreated from a biological system, to enhance modern medicine for better diagnostic and treatment possibilities. As reviewed by Guggisberg, Koch’s [10] probabilistic tractography algorithms can be used to determine the extent of damage to neuronal connectivity following a stroke episode among other rehabilitative techniques such as repetitive transcranial electric stimulation. Of interest, EEG-based BCI architecture has been a tremendous asset in patients suffering from neuromuscular disorders, hence facilitation of simple movement/locomotor remission aided by neuro-prosthetics. Such feats have been developed using noninvasive methods for signal acquisition, bio-signal amplifier and filter to increase the signal-to-noise ratio, exclusion of physiological artifacts, EEG feature extraction and classification as the cue for output using linear or nonlinear classifiers in the form of support vector machines (SVMs), or ANNs, among others [11, 12]. While research is at full steam with respect to BCI-controlled prosthetics, much has been done in terms of platforms used to increase accuracy of the artificial limbs as demonstrated by the application of analyzing the EEG signals using a quadratic time-frequency distribution (QTFD) coupled with a two-layer classification framework to distinguish between individual finger movement within the same hand, hence increasing the resolution and specificity of finger control [13]. Within those lines, Lange et al. [14] processed EEG data using spectrally weighted common spatial patterns (spec-CSP) for feature extraction to correlate it with electromyogram (EMG) recordings for more potent data classification and refined movements. The application of such technology with a neuroscience platform in modern age medicine is inexhaustive.

2. Conclusion

Much progress has been made in the cardiovascular area for coronary abnormality detection inclusive of arrhythmias and infarctions [15, 16], splicing circadian patterns with respect to sleep [17] and fatigue detection [18], prosthetic vision [19], and deep brain stimulators [20], among others. The human-robotic collaboration also forms an intricate and well-established research area for such application, given that commercialization of such products assisting production plants and surgeries are well documented. However, as with all technological innovations, there are certain limitations which are yet to be addressed. Using ML in the field of diagnostic and treatment is always accompanied by the dataset limitation such that the decreased availability of features to be fed into the system can impact on ML performance, especially in disease diagnostics [21]. This is further reinforced by the vulnerability of the system given its dependence on the data used for training; hence, erroneous or biased data will result in flawed outputs. In the case of using machine learning for psychological profiling, the fact that shared symptoms are common across certain mental illnesses, accuracy of predictability would be affected given the nuanced symptomatic classifications [22]. Aside from common methodological factors such as confounding variables and transboundary access to datasets for training algorithms, the major limitation still remains that machine learning cannot as yet include sentient features and thus in the context of robotics-human collaboration or even medical-related decision-making process, implementation of such technology requires further research.

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Chapter 2

Near-Infrared Optical Technologies in Brain-Computer Interface Systems

Korshakov Alexei Vyacheslavovich

Abstract

This chapter presents a comprehensive review of near-infrared spectrometry (NIRS) and related methods, implemented in brain-computer interfaces (BCI). Basic physical principles of such devices are described. Reviews supply readers with summary of recent development in dynamics and perspectives of the field in question. Examples of NIRS usage in BCI systems are provided and different experimental paradigms are described. Review not only deals mainly with noninvasive NIRS-BCIs but also covers some instances of usage of neighboring fields methods (such as EEG, for instance) for the sake of their importance in so-called hybrid BCI systems and/or in fundamental research, which may be less relevant in case of separate application of different encephalographic methods. As potentially beneficial for NIRS-BCIs, the phenomena of fast optical signals (FOS) are described, and some research on connectivity, including those based on NIRS, is covered. Some attention is paid to the perspective for future BCI's construction using optogenetics.

Keywords: brain computer interfaces (BCI), near-infrared spectrometry (NIRS), electroencephalography (EEG), magnetoencephalography (MEG), fMRI, optogenetics, human brain connectivity

1. Introduction

Most of us routinely manipulates of objects in the real world on an everyday basis. But, some people, for example, subjected to severe nervous system damage, may lack this necessary and basic ability. On the other hand, we may not limit our objects manipulations only with hands, but imagine some external actuator, not a part of a human body, but still controlled by one's will and suitable for the specific target manipulation. Such a substitution or addition of a human's abilities is certainly welcomed in the modern world. And although mentioned, the idea seems to be tempting, and its development was suspended for a long time because of difficulty in solving key component of the problem. Key component here is as precise as possible interpretation and transmitting commands born in human mind to external device of any sort. This task can be accomplished at some level by brain-computer interface technology (or BCIs for short). BCI problem was stated several decades ago. Since then, a lot of ground has been covered, yet a lot of discoveries are still ahead.

In present time, there are many "types" of BCIs build on different principles. Among many varieties of BCI, we are willing to emphasize on one, based on registration, interpretation, or classification of activity patterns of human cerebral cortex, registered by the means of one of the existing encephalographic methods, as the most popular. There are other paradigms, but only one is mentioned that allows to build BCI realization based on most encephalographic methods, such as electro-encephalogram (EEG), magnetoencephalogram (MEG), fMRI, and so on (for example, see [1] of MEG realization). Not all of such realizations are of practical value due to usually bulky design. Additionally, we need to consider a family of new encephalographic methods, "fully" developed relatively recently, based on light propagation and interaction with living tissues. Light here must be considered in a wide sense—as radiation of different wavelengths (i.e., visible, infrared and—something in the middle—near infrared). As such, the near-infrared spectrometry method can be introduced, providing yet another way to achieve scientific and practical goals and get additional fundamental results on nervous system.

2. Theoretical bases of near-infrared spectroscopy in biological measurements

Measurements of a substance's characteristics and its complex properties by the means of observing radiation passed through mentioned substance are not a new concept—X-ray imaging is common in medical practice nowadays. Similarly to imaging in visible and plain infrared range of electromagnetic (EM) spectrum, NIRS imaging method utilizes light of near-infrared range to obtain information on tissue properties. In present, there are widely used "optical" (mostly near-infrared—2100–2400 nm wave length range) pulsometer for measurements of heart rate and measurements of glucose level [2–5]. Probing to obtain more "deep" biological parameters is beginning to be routinely implemented, e.g., measuring cerebral oxygenation during cardiac surgeries and in BCIs as a next step.

In general, all infrared range of EM spectrum can be conditionally divided in three subranges: near (λ = 740–2500 nm), middle (λ = 2500 nm–50 μm), and far (λ = 50–2000 μm). Relatively, low radiation absorption by tissues of human body is a distinctive feature of near-infrared range. As a result, for NIR light, one may observe bigger penetration depths—up to several centimeters (maximum 3–5 cm) [6–10]. Thus, some types of biological tissue, to a certain extent, are virtually transparent for named spectrum range. Nevertheless, during light propagation in tissues, elastic scattering processes are very strong and that sets limits to penetration depths on the other hand. In these conditions, beam weakening can be explained predominantly with isotropization and measurements on adult humans, for example, possible only in "reflected light." "Permeate light" measurements are still possible in some cases. For instance, in infants, NIRS method can be applied to diagnose birth brain damage and detectors of NIRS equipment can be located on the opposite (in relation to light sources) side of infant head [11]. This is possible because of the higher optical transparency of infants' bones, skin, and skull covers. One must admit, however, that case mentioned above is certainly not a "BCI application" for several reasons.

All those factors and frequently relatively large value of optical density of biological matter limits our ability to obtain sharp, contrast, and precise images of small (such as mm-size voxels in fMRI) probing volumes. We must, however, stress the fact that this is true only for today's technique and technology.

Nevertheless, one can obtain the estimation of chromophore concentration distribution in a little bit large volumes (usually several cubic centimeters) and thus obtain image of chemicals distribution in targeted tissue [10, 12]. That is sufficient for many applications, including various types of BCIs.

Selection of chromophores (i.e., physiologically relevant substances) depends on light sources' wavelength built in specific piece of equipment. Certain wavelength guarantees preferred interaction of light with chromatophore, structurally important for specific biological tissue. From the physiological point of view, among most important chromophores, one can name hemoglobin, glucose, myoglobin, and cytochrome-c-oxidase [13].

Overwhelming majority of NIRS medical devices, also applicable for BCIs, are designed for cerebral hemodynamics measurement purposes. These devices use 735–760 and 810–860 nm wavelength light sources for target deoxygenated hemoglobin and oxy-hemoglobin correspondingly and utilizes so-called continuous wave experimental paradigm, meaning measuring only power reduction of light beam at detectors, passing through highly scattering mediums, in comparison with initial power, generated by sources [14]. Time delays, phase, and frequency parameter changes are neglected, although there are exceptions [9, 15]. "Continuous wave" device allows building "images" or distribution maps of oxy- and deoxyhemoglobin concentration changes, and measures tissue oxygenation index (TOI) and normalized total hemoglobin index (nTHI) [16].

One must notice, how close such a hemodynamics activity observations make NIRS related to fMRI BOLD. Both methods measure blood oxygenation levels in their own way [6, 9].

NIRS devices itself, usually, consists of one and up to several tens of light sources and detectors. Each possible pair "source-detector" forms a "channel" informative or not; i.e., whether it passes through zone where intensive neural activity is occurring or not and whether emitted by the source-optode light fades away passing through tissues or not. Analog-digital converter (ADC) read detectors' output and after filtering and preprocessing, usually conducted in the form of moving average filter to filter out heart beating, respiratory slow waves, and other nonphysiological artifacts and information about hemodynamics of volume, located "in between and a little bit in depth" in relation to selected source-detector optode position, ready for analysis. Inevitably on the path from source to detector, a portion of radiation will be lost in tissues and will never get in the detector. The other portion diffusely reflected from target volume will be weakened and get in to detector, where it can be quantitatively estimated [17, 18].

Layout of sources and detectors in a manner, when the distance between them is approximately 3 cm on the scalp surface, allows ensuring probing depth of 3–5 cm, sufficient for detecting an activation of human brain cortical areas, although this occurs indirectly, through metabolic effects. Intensive neural activity (usually well differs from background activity) is a process accompanied by oxygen delivery, its absorption by neurons, and evacuation of metabolic products [18–20]. Interpretation of such activity is practically basic of any BCI.

On the other hand, such a set up allows conducting EEG measurements in parallel with NIRS and in the direct proximity of NIRS channels. This is a key for building so-called hybrid BCIs. In principle, in hybrid BCIs, not only and not exclusively EEG can be applied, but EEG is most popular, simple, accessible, and technically usually does not disturb functioning of NIRS devices in any way and vice versa.

Among all methods to describe light propagation in matter, one must notice at least two. First, radiative transfer equation (RTE) (and its various approaches, like diffusion approach) is precise, but difficult to handle and almost impossible to solve for relatively complex problem types [21]. Second, on the other hand, is the phenomenological "modified Beer-Lambert law," specifically "designed" for simplified description of light and radiation, in general propagation in turbid media [22, 23]. Brain and its covers from the NIR-light viewpoint can be considered as possessors of strong turbid properties. As such, the law states that weakening on initial beam depends on value of extinction coefficients, treated as constants, specific for every chemical or chromophore, like both oxy- and deoxyhemoglobin and other [24]. Due to individual scattering acts of spreading photons, their path from entry point to leaving point from turbid media is curvilinear. The so-called differential pathway factor (DPF) serve the purpose of description of this phenomenon in modified Beer-Lambert law. The law in question must be used with caution, and some attention must be paid to borders in which mentioned coefficients variate [25]. Neural tissue has extremely rich blood microcirculation [19], which makes modified Beer-Lambert law at the scale of those blood flows, desired for observation, look like rather a gross approach. In reality, NIR-light interaction process with hemoglobin molecules is much more complicated. For instance, hemoglobin itself has a complex molecular structure and thus influences light scattering and absorption (scattering particles form factor). In addition, hemoglobin molecules are not free blood elements, but are included in dynamically changing structured particles—erythrocytes, which chaotically move in blood stream and in turn have their own form features [20, 22, 26]. All these factors on the microlevel play important role in scattering and absorption processes, but on today's observable scales allowed by modern equipment (1–5 cm in linear dimensions), they hardly can be called significant. This makes modified Beer-Lambert law applicable to described class of problems.

Tomography of cranium in NIR spectrum at present virtually is not widely implemented, especially in context of application of BCIs considered here. Among the reasons of such state of affairs are poor quality, images resolution, with demanding of opposite, and some other general restrictions. Although technology is itself promising and some pieces of optical tomography equipment exist, it can be explained by significant complexity and yet not sufficiently developed by mathematical methods of tomographic image processing, acquired in NIR wave length and as well by some technical difficulties. Nevertheless, some approaches to the problem's solution exist (for example, see diffuse optical tomography or DOT [27–30]).

Ongoing perfection process of scientific equipment, mathematical, and technical measurement methods allows now to detect some signal features, which were impossible to observe before. In particular, there is some research conducting on so to speak "portability" on NIRS, methods earlier developed for detecting evoked potentials essentially by the means of EEG. Among such researches, one may notice [31–35] reports on recording of so-called fast optical signals (FOS), which in terms of authors exactly are optical analogue of low latency EEG that evoked potentials. Reliable registration technique of such phenomenon will allow creating NIRS BCI based on evoked potential paradigm.

It is also necessary to mark fundamental research in the field. A good example of such makes research on connectivity, conducted with NIRS [36, 37]. It may give an additional data always needed during constructing applied equipment for specific tasks, for instance in clinics for poststroke or neurotrauma patients, where brain activity patterns suffer serious changes, and in healthy BCI's users. Generally, research on connectivity of different cortex regions allows to detect not only groups of NIRS channels registering activity specific to the BCI task, but also allows to assume channels, say, with relatively high noise levels as informative, and thus produces more information to identify activity pattern and hence increases BCI system performance. This is also true regardless to modality of registration: NIRS, EEG, etc. Information on connectivity at the stage of development (testing and adaptation to some group of individuals or to a single user) of particular BCI system, can, for example, ease such calculatively difficult process as channels selection. This means inclusion in and/or exclusion from consideration, channels with informative or less informative data output. Otherwise, channels selection procedure require of execution of some usually complex searching algorithm, often time-consuming. Such process of relevant channel selection leads to increase BCI target state classifiability for it is sampling most informative channels, related to task at hand [38].

Resting-state connectivity research is also beneficial as it allows developing approaches and methods, needed for understanding of cortex regions' interrelations [37]. Similarly, functional connectivity research allows understanding interrelations during some task performance. Registered activity patterns are not stable in their nature. They undergo a fluent and perpetual change. Thus, understanding of their spatial and temporal interrelations; i.e., connectivity, probably will allow predicting or at very least mark their changing borders during mental task execution. As a result, such consideration may allow increasing BCI functionality and stability in general. As a good firm method for connectivity research, one must name independent component analysis (ICA) [39, 40]. ICA capable to separate whole data to a set of spatially and temporarily independent components, thus, allow separating useful, informative data from noise and artifacts (such as oculographic artifacts produced by eyes movements) and increase BCI performance. It can be used for better or more precise relating electrical or metabolic, i.e., NIRS-registered activity to a specific cerebral cortex region and hence to a mental state. For example, ICA component with localization mainly focused in motor regions, by association can be viewed as a reflection of some motor act or motor act imagination [41]. Alternatively, localized in Broca area, ICA components signalize of acoustic perception [42]. Among others, processing methods may be useful methods for signal separation in spatially and temporal localized components or for specific process-driven components, one should mention empirical mode decomposition method and its modifications [43, 44].

In relation to connectivity problem in research, one must also notice usage of repetitive transcranial magnetic stimulation as a more invasive measure [45].

Speaking of fundamental research and role of optics in brain research, one must mention optogenetics—quickly developing field utilizing light (of NIR range in some cases) to activate and/or observe genetically modified neural tissues [46, 47].

It will not be far from reality to say that besides those interesting and rapidly developing fields, there are plenty of room for evolution in conventional NIRS-based and hybrid BCI. NIRS-based BCI and imaging technology have many advantages. Among them, one may name noninvasiveness, safety for users, portability and not in the last turn—fairly low price in comparison, for example, with fMRI setups.

3. Material's analysis basics

In order to evaluate present day level of research in the field in question, one must in some way characterize ongoing work, information on which conveys for scientific community through existed papers. To accomplish such a task, one must bring in some form of classification for those objects. Thus, carried out by the general analysis of texts and analysis of keywords, we come up with publications' hierarchical classification system. This classification system forms framework in which the further information is organized (see **Table 1**). This classification system was constructed by the analysis of available papers and their keywords, most often used in them. This system is "emergent, "i.e., was formed on precedents. In event of occurrence of publication, which is not related to one of already existing categories in hierarchy, the new category was reserved. Roots of a tree of hierarchy are the

General type (subtype #1)	Experiment type (subtype #2)	Hybrid type (subtype #3)	Observation area (subtype #4)	Result type (subtype #5)	Additional type (subtype #6)
Reviews	Real BCI experiments description	NIRS only	Motor area	Review's statements	Nothing special (reviews or methodical works)
Real functioning prototype of BCI over ERD paradigm	Classical experiments (finger tapping, memory tasks)	EEG only	Frontal & prefrontal area	Success!	Only one type of experiment described
Real functioning prototype of BCI over EP paradigm	No experiments described in detail	EEG + NIRS hybrid	Temporal area	Failed to achieve success	Several types of experiments considered (motor area, Broca area, etc.)
Unique method description	Nonclassical experiments	Other hybrids (not an EEG + NIRS)	Occipital area	Failed to achieve success, but there is a hope for the future	One type of experiment described only, and indirect fundamental conclusions were drawn by results
	FOS	EEG only, but some hybrid declared (+NIRS)	Something else (For instance, EEG over motor area, NIRS—over frontal area)		Robot control
		Just about everything in existence			Article about a choice of classifiers, usage of exotic classifiers, research directed on improvement of work of classifiers or algorithms of a choice of features
					Paper about technical aspects of NIRS of equipment designing
					Paper about experiment with a big deviation toward technical details of instrument and equipment
					Modeling of neural activity/ hemodynamics

Table 1.
Hierarchical emergent classification system.

basic types of the publications, for example, whether article is the review, whether it represents the description of real experiments in ERS/ERD- or EP paradigms (event-related synchronization/desynchronization or evoked potentials), or it represents the description of a new unique method of research.

The second subtype was formed by types of described experiments, such as: real experiments on functioning model of BCI, the description of "classical" for NIRS experiments (for instance, various memory tasks, finger or a palm tapping, mental arithmetic), etc. The last category was related to "not classical" experiment, i.e., mental tasks or problems solving and were rarely or not published at all earlier. A separate category of the given subtype has been allocated as fast optical signals (FOS) or "optical evoke potentials" registration with or without signal averaging and so on. Researches on connectivity and optogenetics were not included in classification system and were treated separately, for they constitute merely a support value in the BCI context.

The third subtype was whether the considered one in article BCI was a "hybrid." Along with separate EEG and NIRS measurements, there are papers on hybrids of EEG + NIRS and hybrids of other nature, for example NIRS + fMRI out there.

The fourth criterion of classification was the brain area over which measurements were conducted (for example, motor areas, frontal and prefrontal areas of human cerebral cortex, temporal area, an occipital cortex or something else, for instance EEG-measurements were conducted over motor areas, and NIRS measurements—over frontal and prefrontal areas).

The fifth criterion was whether there is an achievement of the goal or objective declared in the paper, i.e., whether work can be treated or treated by authors as success.

At last, the sixth subtype of hierarchical emergent classification was devoted to papers in which some special characteristics or unique feature were presented. Among such features were "how many types of experiments were described and conducted in work, reported by the paper" or whether BCI was used in work for management of the robot or external assistive actuator, etc.

Certainly, the given classification is not complete and a closed system. Also, it is not unique. However, its application is quite justified, since, at least, it is "to some extent" stable, i.e., robust and stable to the new information addition. It is possible to come to such a conclusion, having taken into consideration fact, that actually the classification structure has ceased to change after processing only of about 25 publications from the considered pool, chosen in a random manner. Also, it is necessary to notice that there were some categories which by their nature have not been presented in a considered pool of publications during analysis, but were included in (or better to say drawn into) classification system. For example, a class of articles telling about distribution of light propagated through a biological tissue and physic properties of this process, FOS, which only indirectly connected to BCI, and so on. Focus of such articles is displaced aside from practical applications of BCI to general physical laws on the basis of which any of NIRS devices are constructed and to fundamental research of nervous system. Nevertheless, some processed papers can be additionally classified with the last category, yet bearing in mind the fact of their distant relations to the main subject (i.e., distant from the roots branches) of classification system described.

4. Latest achievements in constructing BCI over NIRS and "hybrid" BCI

Research presented here provides with a detailed analysis of over 100 articles with various time of publishing. Total number of papers under consideration, possibly only indirectly connected with BCI subject, but connected to the related fields, was 178. Some of these papers used NIRS equipment in BCI applications, or for the comparative analysis and test for reliability of NIRS data versus fMRI-BOLD, or for other fundamental or technical purposes. The earliest publication that has come into the view was dated by 1993, the latest by 2017. Thus, this affirms that research of a human brain and nervous system utilizing NIRS is a new and fast developing field of science. Data confirm this statement as shown in **Figure 1**, where it is well visible, that the dynamics of number of publications on past years shows general growth. The year 2017 and beyond, of course, at the moment is not indicative and can be analyzed only in future in retrospective. Despite this, due to the increasing interest to NIRS, to BCI technology, and to related fields, the tendency will most certainly remain.

Among types of experiments, leading position (by number) is occupied by papers in which experiments in both ERS/ERD—and EP paradigms were described. Among them, there was some number of papers about classical type experiments (i.e., accepted and well known in cognitive research, for instance mental arithmetic). Smaller, but nevertheless the noticeable share constitutes publications in which there were no detailed descriptions of experiments, or they were not conducted at all. Still smaller portion describes “nonclassical” experiments. See [48] for experiments, where motor cortex activity was recorded, in which movements done by the person peeling apples were described. Paper [49] describes BCI, one of which states the intention of the user to carry out “speech activity, “i.e., intention to say something. Such state was utilized as a sign of examinee’s wish to use the BCI system. Recognition accuracy of such mental state reaches 73%. Segments of NIRS records, in which the examinee pronounced words, can be distinguished from “rest state.”

Smallest party was formed by works published on an FOS, connectivity, and optogenetics, but last two were viewed more like as an addition here.

Despite the obvious advantages widely described in the scientific periodic literature, hybrid BCIs are just not exclusively popular. BCIs over NIRS-only are leading by quantity of publications (at least in considered pool till 2017 year). EEG + NIRS hybrids actually take only the second place. The third occupies BCI over EEG only, still containing a considerable quantity of references to work with NIRS. The remaining numbers are made by articles with description of BCI over EEG in which the future research in BCIs over NIRS was declared or with the comparison works of two technologies. Papers in which hybrid BCI over NIRS and some another “modality” (other than EEG) was described constitutes the smallest pool. Distribution of publications by quantity according to these properties is resulted in **Figure 2**.

Areas over which usually NIRS optodes and/or EEG electrodes were situated correspond to type of a mental task, which is planned to work with in particular experiment.

Figure 1.
Number of publications on “NIRS” by years.

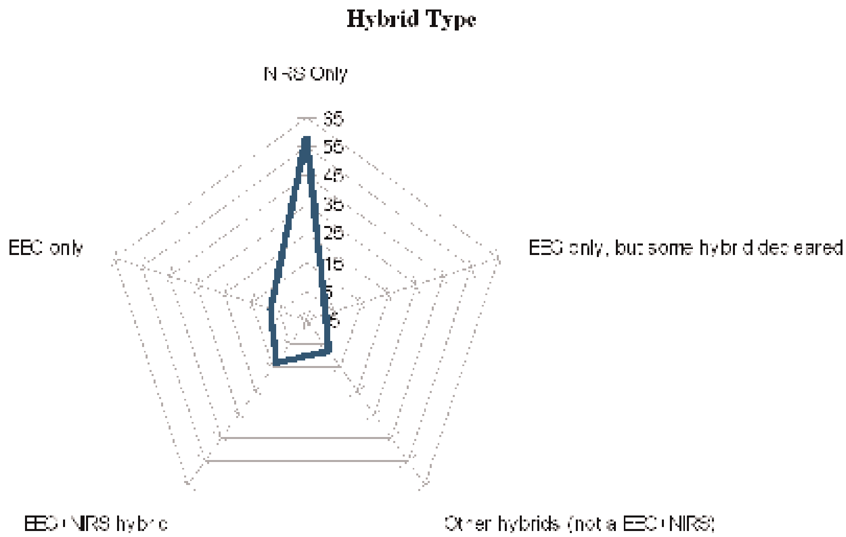

Figure 2.
BCI hybrid type (papers types & count).

So for, imagination of movements and tapping the motor areas corresponds, for cognitive tasks—frontal and prefrontal cortex areas, to visual recognition, naturally—an occipital cortex. Experiments with auditory system, for example, definition of the fact of audibility of a sound, pronouncing of internal speech, demand registration in temporal area and prefrontal cortex. All these ways of registration are traced in articles of a considered pool. In all those experiments, hybrid registration also took place. Usually, EEG recording was conducted over motor cortex, and NIRS recording was conducted over frontal and prefrontal areas. Most papers fell into this category—almost 44% from the general number of publications. Proceeding from experience of NIRS registration, it is supreme strategy of BCI construction since it gives possibility of simultaneous EEG registration of event-related desynchronization of brain rhythms, providing advantages in time resolution, and, reliability of NIRS cognitive answers. Preferences of registration areas, and, hence, to experiment types are illustrated in **Figure 3**.

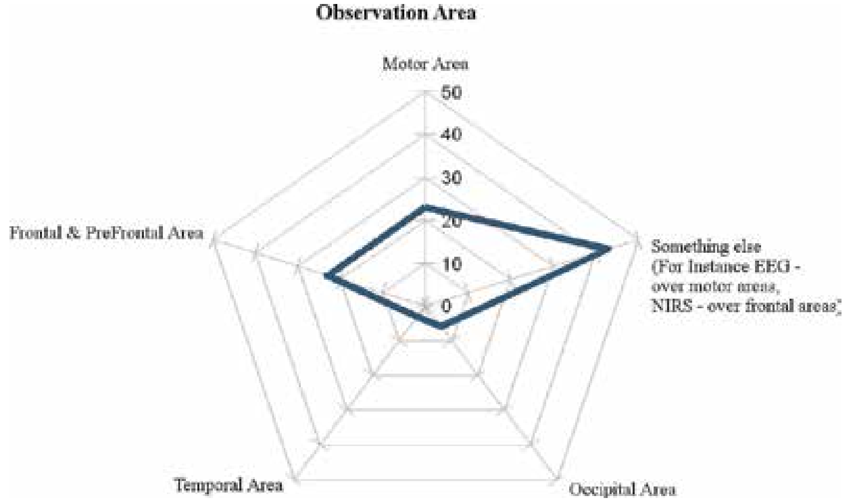

Figure 3.
Registration areas (observation area type & paper count).

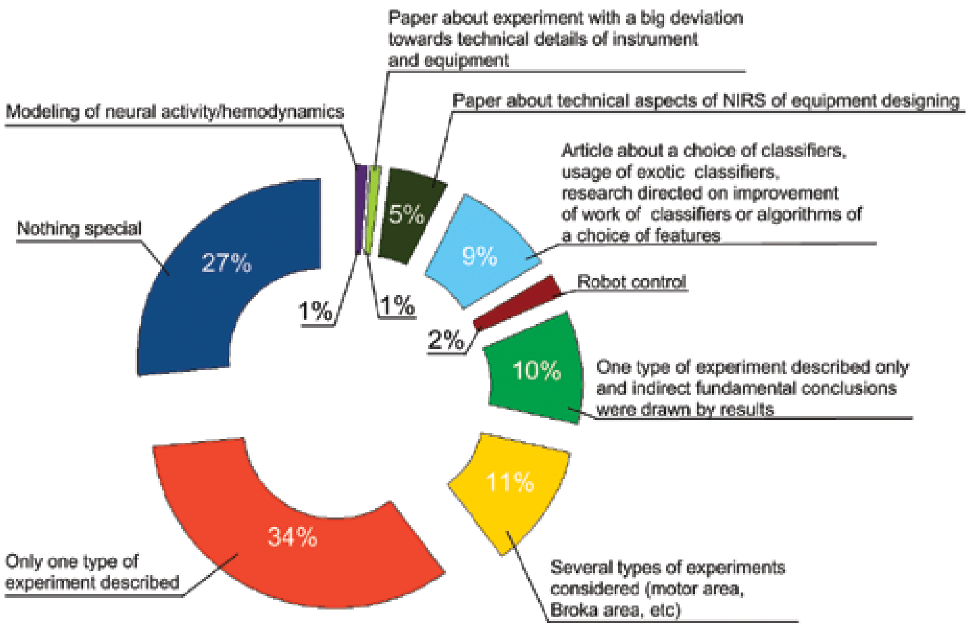

Figure 4.
Special features of considered papers.

By this analysis, one can say that the most number of papers represents publications of work results upon only one—“pilot” experiment with NIRS or with hybrid modality. Equivalently, a big share constitutes the works, which do not have any outstanding properties (mainly its reviews, and also the works, results of which have descriptive or methodical properties). Third place by frequency of occurrence is divided by works in which different types of experiments were conducted and by works in which some fundamental conclusions were drawn from those results. Articles about mathematical features of BCI application or about classifiers of NIRS signals form another category. Here, papers on choice of signals’ features selection algorithms are also included (including automatic feature selection).

The remaining small part is made by articles devoted to technical aspects of BCI over NIRS devices and systems construction, control of assistive robots and external actuators, and artificial limbs. Hereby, NIRS begins to connect with innovation process in area of anthropomorphic mechanisms designing in addition to medicine. One also must note articles on hemodynamics studying. Such situation can be generalized by phrase: “NIRS only starts to extend to those directions.” Mentioned features of a considered pool of articles are illustrated in **Figure 4** (for explanations of section names, see **Table 1**).

5. Particular examples of BCI on NIRS and hybrid BCI

Let us now introduce description of some interesting specific examples on considered device type. One should see [50–52] to know about technical features and designs of NIRS devices and applications. It is possible to read about potential of commercial application of considered technologies in [53]. Paper [54] represents the review of the most recent achievements in the field of BCI uses in rehabilitation of poststroke patients with a stress on methodology, which pointed out that results of such rehabilitation led to improvement of the patients’ motor act. Some challenges and unresolved problems are also discussed. Efficiency of NIRS-BCI was compared in relation to implementation of visual feedback and placebo as a feedback. The first case has shown motility substantial improvement. In [55], NIRS research of Broca area for purpose of Chinese language vowels internal pronouncing recognition was conducted. Paper represents an attempt to introduce a measure of consciousnesses presence for the paralyzed patients and patients with a locked in syndrome (LIS). The study was constructed around concept of "consciousness index" and attempted to introduce objective numerical criterion of consciousness presence in the patient.

Work [56] was devoted to various types of mental task usage efficiency estimation in NIRS-BCI. Till now, studies in the field of NIRS-BCI have been focused on increase in accuracy of various mental tasks' classification. In the given paper, search of mental states pairs which would be the best from the point of view of BCI customization, i.e., best classifiable in given conditions. In event-related hemodynamic response on eight channels, NIRS system had been recorded for various mental tasks in seven subjects. The beginning of a condition simulation for the examinee was designated by sounds followed by a 15-s pause for elimination "aftershock" in hemodynamics caused by sound. The pause between trails varied from 10 to 15 s for elimination of accustoming effect. Mental conditions or states under investigation were the following: LMI—left motor imagining (i.e., imagining of motor activity by the left arm), RMI—right motor imagining, FMI—foot motor imagining, SING—mental singing, SUB—sequential subtraction of small numbers, MUL—mental multiplication, ROT—mental rotation of a given three-dimensional (3-D) geometric figure, and WRT—mental character writing. Based on this approach, a set of "recommended" mental tasks with rather big classifications accuracy represents the following list: "mental multiplication," "mental rotation," and "motor imagination of the right hand." Pairs, formed of any two mental states from three listed above, show the highest mean accuracy of classification by utilizing method of linear discriminant analysis (LDA), most used in BCI applications, as authors stated. Authors of article expect that their results will be useful to reduction of time spent in research, technical, and methodical works, on definition of the best individually specific mental conditions, and their combinations. LDA, as classification algorithm, utilized three features: oxy-, deoxy-, and full hemoglobin. Naturally, choice of the best mental state was made upon the best distinguish ability of LDA algorithms. Also, it was stated that selection was influenced by searching on channel position dependencies, i.e., searching the most informative channel.

Often, the most natural to the examinee was the imagination of movement of their own hands and that is applied in many BCI systems based on an ERD/ERS paradigm. Work [57] represents research and the proof of fact that imagination of right and left hand movements produces distinguishable patterns of hemodynamic activity, which can be classified with the linear classifier and, thus, applicable in BCI systems. Conditions of experiments are rather a standard scheme nowadays: 10 healthy examinees, kinesthetic imagination, inflections of the left and right hands, and command indications were presented on the computer screen. Signals from right- and left-lateral motor cortex have been registered simultaneously with the use of multichannel NIRS system of a continuous wave type. Linear discriminant analysis was used as the classifier, which has allowed achieving an average on examinees classification accuracy of 73.35 and 83.0% for the right and left hands, accordingly.

In works [58, 59], classification of multichannel "NIRS patterns" is considered for states of motor imagination in order to construct BCI for people with the limited abilities. In work [59], the previous studies of other authors were mentioned in which other paradigms were also considered, for example, imagination of movements and recall of specific emotions, concentrations, and electric stimulation (reaction to it). The general scheme of classical experiments, information gathering, signal reception, choice and extraction of features, and a command/classification estimation is described. The detailed description of NIRS signals processing is resulted; trends, typical for NIRS signal, and ways to obviate them by means of averaging were also mentioned, and two types of averaging were applied. Some theoretical aspects based on NIRS were given, such as explanation of nature of changes in hemodynamics, accompanied by neurons activity. Problems of influence of respiratory cycles, Mayer's waves, and heart responses described were also considered. As reliable methods of a noise reduction in NIRS, general linear model (GLM) and ICA were offered and used. Main objective of this paper was to find a difference between an "active" (i.e., "key-") and "passive" mental states using NIRS.

It would be desirable to note also the work [60] in which working out hand-movement-direction-detection methods were described, proceeding from the NIRS hemodynamic response of the motor acts induced by the examinee and registered from motor area. The paper pursues the aim of perfection applications of assistive technologies. In total, 64 specially distributed optodes were used in experimental setup. Examinees had to produce "free" (i.e. with no constraints) hands' movements' in orthogonal directions (x- and y-directions in a horizontal plane). As features, changes in concentrations of oxy-, deoxyhemoglobin, their sum, and their difference were considered. Full delivery of oxygen and its evacuation have been calculated for local neural populations in the motor cortex, which underlaid the optode positions. The analysis of these signals has shown that such movements can be distinguished in space and time depending on a directions of movements. Thus, by analyzing of existed profiles of brain activation, it is possible to identify unique directions of movement of a hand in real time. This work can be considered as a precursor of BCI in which states can be changed slowly or "gradually"; thus, such a device can be termed gradual BCI.

The idea of rehabilitation with the use of the robotized artificial limb has been presented more than 10 years ago. Since then, their clinical reliability and efficiency have been reported in a considerable quantity of works (see [61–63]).

As one can note, branch of research connected with a robotics is a rapidly developing direction inside the basic stream of research in the field related to BCI. In [64], the idea of NIRS usage in robot management and possibility of its technical realization is considered. Actually, it is the review of the hardware and software complexes realizing the considered function.

Probably, the principal cause of frequent use of the evoked potentials is the simplicity of their registration and the simplicity of mathematical methods of their processing. But, this is not the case with other paradigms. On the other hand, as an example of elaborate methods for signal processing, one may consider the paper [65], where methods of chaotic dynamics were used in order to analyze fNIRS signal in BCI application. The aim was to recognize left and right hands' motor imagery. Authors also used principal components analysis for the exclusion of high-frequency noise signals and mutual information criterion for some windows of signal. The aim of this paper is to investigate the chaotic property of hemoglobin changes of the blood within motor cortex by Lyapunov analysis. Such a result was achieved—the paper stated that NIRS signals have chaotic properties.

In [66], the noninvasive BCIs for use in neuroprosthesis are described. Works in the field of EEG indicate that the big accuracy and stability for such BCI are essential. The question of whether NIRS method is capable to improve BCI based on EEG was discussed in the paper. Both the methods have been applied simultaneously to record sensomotor rhythm. Research includes work with real and imagined movements. Results of work say that simultaneous EEG and NIRS records can essentially improve classification of motor imagination accuracy up to about 90%, on the average, having an improved accuracy indicator on 5% ($p < 0.01$) in comparison with the use of EEG only. Thus, the concept of hybrid BCI had been introduced. Nevertheless, the long delay of the hemodynamic answer can interfere with the improvement of the general accuracy of classification. Moreover, authors have found out that NIRS and EEG complement each other in sense of the information capacity. Therefore, those methods are applied together and are reliable multimodal imaging techniques. The 24-channel NIRS was used in which readings were averaged in time. As features, classifier LDA was used. It appeared to be that results of classification for EEG and NIRS correlate, but with some time lag that is connected with the NIRS nature.

The low time resolution is an essential lack of NIRS, and it is underlined in number of works, including with orientation to practical application of BCI. In [67], it is noticed that work of any BCI over NIRS is accompanied by a delay in several seconds that limits practical application of this system in a real world. Here, support vector machine (SVM) classification method for definition of a true mental state (finger tapping and rest) was used. Estimations of various spatial features' efficiency, such as signal history, history of a gradient of a signal, and spatial distribution of oxy- and deoxyhemoglobin, are resulted. It is revealed that the delay for decoding of changes in a behavioral condition can be reduced to 50% (from 4.8 down to 2.4 s) that essentially improves indicators of BCI over NIRS. Results of classification in terms of accuracy that reached depending on a set of features applied were considered. Maximum achieved accuracy was 87%.

It is necessary to note the work [68] in which NIRS was used with fundamental purposes. The quality of the evoked potentials in the visual cortex was studied in dependence of age of the examinee. Two groups of examinees were considered by age about 21 and about 71 years. Both groups have shown increase in change of concentration of oxygenated hemoglobin and in reduction of deoxygenated hemoglobin during stimulation by a visual chess pattern. However, people in their 70s, on the average, gave more variable hemodynamic answer and often had comparable level of hemoglobin concentrations during time of stimulation versus rest condition —a base line. More young people had essentially high concentration of oxygenated and deoxygenated hemoglobin in each test without dependence from type of stimulation ($p < 0.05$). Average variability associated with effect of age has made 88% on oxygenated and 91% on deoxygenated hemoglobin. Experiments with visual stimuli has shown rapid falling of cortical hemodynamic answer with age, independently from stimulus' parameters. Thus, authors do the conclusion that hemodynamic answer can be treated as age characteristic. Area V1 was studied. Results were analyzed with ANOVA.

Works [69–73] were devoted to cognitive research, namely "memory" group; besides in [74], methods of psychology for improvement of BCI performance were used. In [70], patterns of hemodynamic activity build-up estimation during perception of numbers by examinees ("mental arithmetic "task) were investigated. Researches used NIRS with high optode density in scalp positioning (348 channels), and standard mathematical methods of preliminary signals processing were applied. For features' selection, applied algorithms were used, which governs the choice of the best channels or a best feature set. Thus structure of classification features in array of channels were reduced and varied for better BCI performance. One can name this as "greedy" algorithm; also, the combined algorithm with cutting out superfluous features is considered. The effective number of channels for classification, therefore, was reduced. Classification was made by SVM; and accuracy of distinction of "difficult mental arithmetic tasks" from a rest condition reached about 100%, "easy mental arithmetic tasks"—also about 100%. Check of reliability concluded the result.

Ref. [75] is a typical example of papers concerning methodical maintenance of NIRS experiments. Research focuses on developing a method for choosing effective training data sets for BCI training. In particular, BCI was considered for definition of concentration of examinees during experiment. This research also was devoted to integration of EEG and NIRS for their joint usage in "cognitive level" BCI applications. This term designates level of the interest of the examinee in experiment process. For construction of such interface, the paradigm based on P300 evoked potential was used. In this work, two experiments are presented: first—the mathematical task with NIRS-only measurements took place. Hybrid EEG + NIRS was used under EP paradigm (P300), and BCI system of type "ON-OFF machine" was constructed on its basis. Experiments had shown that with the use of NIRS, it is possible to differentiate concentration conditions (mental activity) and to distinguish them from level of mental rest. The second experiment, however, has revealed essential and statistically significant result only in EEG.

As for the struggle against artifacts, Ref. [76] brings it on a new level. The work sets as its purpose working out methods of artifacts cutout and implementation of those methods. Not only artifacts of true or "internal" physiological nature were considered (such as relatively stable heart beating waves, appearing on HbR and HbO concentrations' changes curves), but also artifacts of physiological nature, caused by external factors. For example, there were considered changes in signal, conditioned by sudden attraction of attention to external objects or conditions. A number of external distracting factors, in particular, sharp sounds, distracting noise, are considered. The whole purpose of this work was to develop compensation for distracting factors, for NIRS-BCI to satisfy practical conditions. In the article, the system of filtration of the mentioned types of the artifacts based on hidden Markov chains (HMM) is considered. In [72], struggle against artifacts was carried out by medicamentous methods—by the local application of vasodilator drug.

One of the techniques directed to improvement of classifiers functioning within BCI is the utilization of so-called hybrid BCI in which signals about a condition of the examinee were received by means of at least two devices of various modalities [51, 66, 76–81]. In [81], the concept of hybrid BCI in general—not only in sense of various modalities, but also in sense of various paradigms of record (ERD/EP), was introduced. The basic criteria of such device with reference to practice were given. The necessary quality standards were discussed. Various types of BCI, for example "the brain switch," were considered, basically focusing on an artificial hand limb, which operates by means of EP.

One can consider [82] as a good "head first" text about nervous processes studying techniques. Here, it is noticed that NIRS possesses the low time resolution and can even interfere with transitions between conditions. To cut out this lack, it was recommended to use it together with EEG. In general, the article affirms that the BCI based on NIRS are inexpensive, but does not show high-quality results. Various methods of preprocessing (CAR, SL, ICA, CSP, PCA, SVD, CSSP, FreqNorm, LAT, LKF, and CSSD) are considered and estimated. Most often used are ICA, CAR, LS, PCA, CSP, and adaptive filtering. In this paper, the hybrid BCI on the basis of NIRS and MEG were also mentioned and also stated that they are disproportionately expensive, considering achievable results.

FOS responses [31–34] do not directly relate to BCI, but nevertheless were considered for a possibility to build optical EP BCI based on such phenomena. FOS usage can increase "reaction time" of hemodynamic responses and hence can improve NIRS-FOS BCI performance. FOS registration demands extreme temporal resolution on NIRS equipment. Analogically, research of correlation with fMRI also difficult in that sense that fMRI-BOLD signal with "reception" time about 2.5 s has no sufficient time resolution to obtain information on "fast" reactions.

Nevertheless, it is a very interesting problem, which can be solved only with the use of a multichannel and high-frequency NIRS with superb parameters.

In [33], authors demonstrate that optical methods can be used to detect rapid changes in functional connectivity during cognitive processes.

In experiments, described in [31], animal photos were presented to examinee, who needs to press button, when a picture was “well known.” That is so-called Go/no-Go paradigm. After the experiment was carried out, the map of correlations between EEG and FOS was built. In this paper, averaging of a signal was applied to allocate FOS responses. Thus, Ref. [31] stated that NIRS method is sensitive to hemodynamics of a brain (in the article, the term “slow signals” was used), and as well to fast responses of neural activity, or so-called fast optical signals or FOS for short. Registration of the FOS is difficult due to their nature and assumes low level of signal/noise ratio of experimental setup. Authors managed to register authentically FOS for 11 examinees, simultaneously with EEG registration.

At present, the necessity for more “fine” research on hemodynamic response’s features registered in the NIR modality in order to obtain more detailed description of its features from the point of view of physiology is obvious. In [83], experimental confirmation presented that there is a time difference between hemodynamic answers in oxy- and deoxyhemoglobin. Authors revealed that a time profile of hemoglobin-concentration-change curve is desynchronized; i.e., their levels do not fall, and their sum and the difference do not rise simultaneously. Such measurements can reveal a difference in brain activity patterns, while hand movements in directions left-right and forward-back considered in experiments were described in mentioned paper.

“Connectivity” research can be treated as another example of theoretical research, beneficial to BCI system improvement. NIRS data acquisition systems were introduced here just recently. For basic information about connectivity, see [84, 85].

For information about connectivity modeling and NIRS/EEG phantom construction for testing connectivity models, see [86]. Authors offer “testbed,” i.e., phantom for simultaneous NIRS/EEG recordings for rapid model testing for plausibility, although biological interpretation of connectivity is simplified. NIRS processing software “NAVI” as a part of testbed design was used [87, 88].

For comprehensive evaluation of utilizing NIRS in connectivity research, resting state, and functional as well and especially their dynamic characteristics, one should see [89]. Authors also point to disadvantage of NIRS usage in this type of studies —“low” penetration depth limits research only to cerebral cortex. On the other hand, this may allow excluding off the most low-level nervous functions from the consideration.

Ref. [90] is devoted to the research of functional connectivity of neuronal mechanisms underlying the reactions occurring during experiments in Go/No-Go paradigm, in relation to human development problem. The paper compares such reactions of children and adults examinees, and in particular, comes to the conclusion that motor-related activation did not differ between age groups. This means that at least within the limits of mentioned paradigm, there is virtually no difference in movement realizations and in their control patterns of cortical activity. This statement brings such patterns in position of more universal detectable target, independent from age of examinee.

This can be summarized as ongoing process of initial accumulation of facts and potentially useful information. Their implementation in BCI technology may lead to productive results.

Finally, let us point the reader to optogenetics research [46]. Papers on the subject do not directly relate to BCI technology directly, but more like to neurobiology as a whole. In the context of problem at hand, it makes sense to concentrate on papers, which aims to use some kind of NIRS or optical equipment.

In this way, Refs. [91, 92] describe methods, which utilize NIR radiation in confocal microscope in order of correction and control of neural cell growth. Further developments of this direction can be found in [93], where laser microsurgery of cellular membrane was described.

Ref. [47] was devoted to optogenetics methods of neural cells activation with high spatial precision by making those cells produce reaction when irradiated with light. This is achievable by the means of transfection of cell genome with gene constructs, which corresponds to channelrhodopsin 2 protein. Activation of transfected cells develops upon exposure to light of NIR range (860–1028 nm). Such manipulations may provide a researcher with method of external activation of nerve cells', deeply situated in experimental animals' brain and with high spatial resolution. Experiments in the field also features ability to "read" neurons' activity patterns, induced on purpose. This can be achieved by variation of wavelength and intensity of excitatory radiation. This direction of thought is interesting because it represents fully optical method for monitoring, excitation, and detection of neural activity on the cellular level. One may hypothesize that in distant enough perspective, such a research may lead to obtaining new and more precise data on brain structure, functioning, and connections. Also, new generation of genetically coded voltage sensitive dyes can yield state-of-the-art methods and techniques of acquiring new data on functioning of neuron cells' population level [94]. Alas, in their present state, optogenetics methods are very suitable and useful for fundamental research (usually not even *in vivo*), but they have not yet leveled up with practical demands of problem discussed here.

At last, it is necessary to notice that despite essential successes in the field of construction of BCI and machine interfaces (these are researches that generate about thousands of publications every year), progress in the field of creation of devices would allow patients with a full paralysis and "locked-in" syndrome to interact with an external world, which is, for now, possible to characterize only as moderate [95].

6. Conclusion

Objectively, the quantity of works in dynamics for more than 10 years grows, and the considered area of researches extends. Also, the subjects of papers in the field extend in more details, growing with new data.

The fact that the considerable part of papers in the field is reviews attracts attention. It can testify to the big number of scientific personnel, which began or begin at the moment the work on a considered problem. Also from this number, it is possible to draw indirect conclusions about quantity of scientific personnel.

The offered system of classification of publications was given here in hope that it will be useful for researchers' choice of a direction in considered area and in order to aid more effective development of this direction as a whole.

There are a big number of articles in which only the near-infrared range spectrometry is used (without EEG and other means of neuroimaging) and also the ERD/ERS experimental paradigm most frequent and limited enough circle of cognitive effects was measured.

Researches, in which hybrid interfaces were used in comparison with aforementioned, are scarce. Even less papers concerning fast optical signals, fundamental physiological questions with the use of NIRS or connection of nervous activity, and optical properties of a living tissue and physical features of distribution of near-infrared range radiation in biological substances possess complex structure. Hybrid interfaces are focused mainly on conducting NIRS cognitive experiments (in which some cognitive effects or conditions exploited and responses were acquired with NIRS) in synchrony or in parallel with registration of motor activity with the EEG usage only. There are exceptionally few publications, concerning the technical details and improvement of characteristics of the spectrometer equipment. Technical features are not addressed in detail even in papers that were using devices of "own manufacture." The field of NIRS devices with technical features, obviously, is assigned exclusively to manufacturers of the equipment. The insignificant part of papers, reviewed here, was devoted to the usage of NIRS/EEG BCI in one setup with assistive robotic devices, artificial limbs, and exoskeletons. Due to pressing nature of this matter and under a condition of extraordinary results, occurrences in the near future in this field, obviously the share of such publications, will only grow, probably, involving in the pool of papers on the technical details of such installations as a whole, including NIRS and robotics.

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Chapter 3

Speech Enhancement Using an Iterative Posterior NMF

Sunnydayal Vanambathina

Abstract

Over the years, miscellaneous methods for speech enhancement have been proposed, such as spectral subtraction (SS) and minimum mean square error (MMSE) estimators. These methods do not require any prior knowledge about the speech and noise signals nor any training stage beforehand, so they are highly flexible and allow implementation in various situations. However, these algorithms usually assume that the noise is stationary and are thus not good at dealing with nonstationary noise types, especially under low signal-to-noise (SNR) conditions. To overcome the drawbacks of the above methods, nonnegative matrix factorization (NMF) is introduced. NMF approach is more robust to nonstationary noise. In this chapter, we are actually interested in the application of speech enhancement using NMF approach. A speech enhancement method based on regularized nonnegative matrix factorization (NMF) for nonstationary Gaussian noise is proposed. The spectral components of speech and noise are modeled as Gamma and Rayleigh, respectively. We propose to adaptively estimate the sufficient statistics of these distributions to obtain a natural regularization of the NMF criterion.

Keywords: nonnegative matrix factorization (NMF), speech enhancement, signal-to-noise ratio (SNR), expectation maximization (EM) algorithms, posterior regularization (PR)

1. Introduction

Over the past several decades, there has been a large research interest in the problem of single-channel sound source separation. Such work focuses on the task of separating a single mixture recording into its respective sources and is motivated by the fact that real-world sounds are inherently constructed by many individual sounds (e.g., human speakers, musical instruments, background noise, etc.). While source separation is difficult, the topic is highly motivated by many outstanding problems in audio signal processing and machine learning, including the following:

1. Speech denoising and enhancement—the task of removing background noise (e.g., wind, babble, etc.) from recorded speech and improving speech intelligibility for human listeners and/or automatic speech recognizers

2. Content-based analysis and processing—the task of extracting and/or processing audio based on semantic properties of the recording such as tempo, rhythm, and/or pitch

3. Music transcription—the task of notating an audio recording into a musical representation such as a musical score, guitar tablature, or other symbolic notations

4. Audio-based forensics—the task of examining, comparing, and evaluating audio recordings for scientific and/or legal matters

5. Audio restoration—the task of removing imperfections such as noise, hiss, pops, and crackles from (typically old) audio recordings

6. Music remixing and content creation—the task of creating a new musical work by manipulating the content of one or more previously existing recordings

2. Nonnegative matrix factorization

2.1 NMF model

Nonnegative matrix factorization is a process that approximates a single nonnegative matrix as the product of two nonnegative matrices. It is defined by

$$V \approx WH \tag{1}$$

$V \in R_{+}^{N_f \times N_t}$ is a nonnegative input matrix. $W \in R_{+}^{N_f \times N_z}$ is a matrix of basis vectors, basis functions, or dictionary elements; $H \in R_{+}^{N_z \times N_t}$ is a matrix of corresponding activations, weights, or gains; and N_f is the number of rows of the input matrix. N_t is the number of columns of the input matrix; N_z is the number of basis vectors [1].

$V \in R_{+}^{N_f \times N_t}$—original nonnegative input data matrix

- Each column is an N_f -dimensional data sample.

- Each row represents a data feature.

$W \in R_{+}^{N_f \times N_z}$ —matrix of basis vectors, basis functions, or dictionary elements.

- A column represents a basis vector, basis function, or dictionary element.

- Each column is not orthonormal, but commonly normalized to one.

$H \in R_{+}^{N_z \times N_t}$ —matrix of activations, weights, encodings, or gains.

- A row represents the gain of a corresponding basis vector.

- Each row is not orthonormal, but sometimes normalized to one.

When used for audio applications, NMF is typically used to model spectrogram data or the magnitude of STFT data [2]. That is, we take a single-channel recording, transform it into the time-frequency domain using the STFT, take the magnitude or power V, and then approximate the result as $V \approx WH$. In doing so, NMF approximates spectrogram data as a linear combination of prototypical frequencies or spectra (i.e., basis vectors) over time.

This process can be seen in **Figure 1** [3], where a two-measure piano passage of "Mary Had a Little Lamb" is shown alongside a spectrogram and an NMF factorization. Notice how **W** captures the harmonic content of the three pitches of the passage and **H** captures the time onsets and gains of the individual notes. Also note that N_z is typically chosen manually or using a model selection procedure such as cross-validation and N_f and N_t are a function of the overall recording length and STFT parameters (transform length, zero-padding size, and hop size).

This leads to two related interpretations of how NMF models spectrogram data. The first interpretation is that the columns of V (i.e., short-time segments of the mixture signal) are approximated as a weighted sum of basis vectors as shown in **Figure 2** and Eq. (2):

$$V \approx \begin{bmatrix} | & | & | & & | \\ V1 & V2 & V_3 & \ldots\ldots & V_{N_t} \\ | & | & | & & | \end{bmatrix} \approx \left[\sum_{j=1}^{N_z} H_{j1} W_j \;\; \sum_{j=1}^{K} H_{j2} W_j \;\; \sum_{j=1}^{K} H_{jN_t} W_j \right] \tag{2}$$

The second interpretation is that the entire matrix V is approximated as a sum of matrix "layers," as shown in **Figure 3** and Eq. (3).

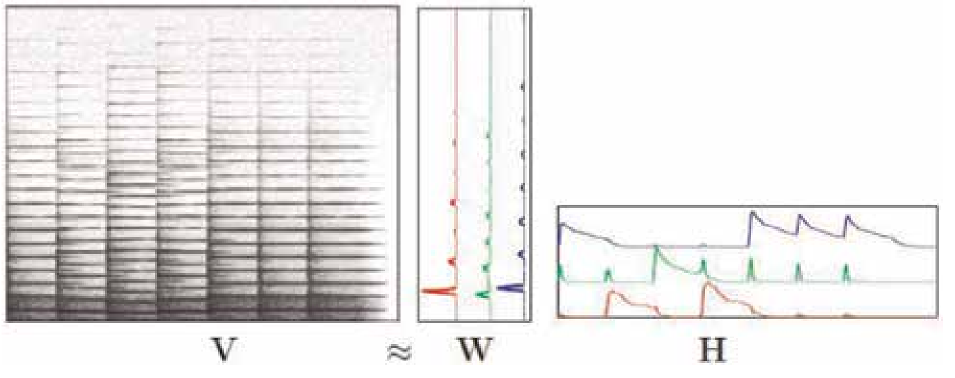

Figure 1.
*NMF of a piano performing "Mary had a little lamb" for two measures with N_z = 3. Notice how matrix **W** captures the harmonic content of the three pitches of the passage and matrix **H** captures the time onsets and gains of the individual notes [3].*

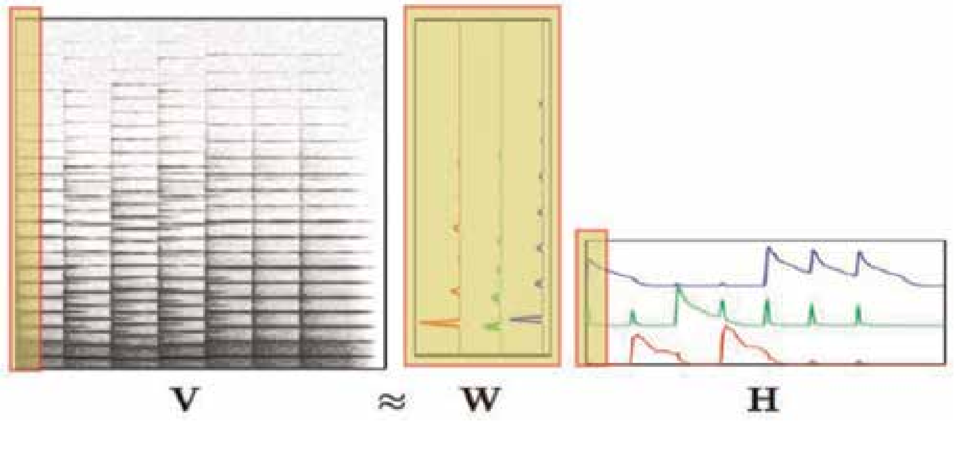

Figure 2.
*NMF interpretation I. the columns of **V** (i.e., short-time segments of the mixture signal) are approximated as a weighted sum or mixture of basis vectors **W** [3].*

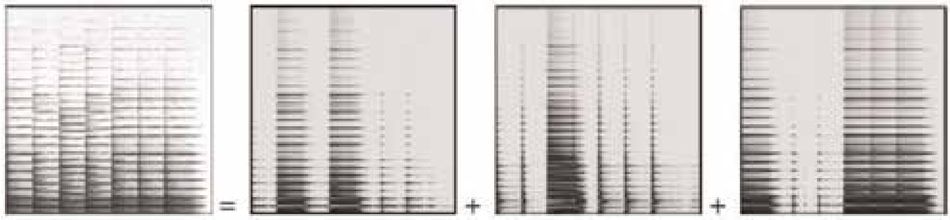

Figure 3.
*NMF interpretation II. The matrix **V** (i.e., the mixture signal) is approximated as a sum of matrix "layers" [3].*

$$V \approx \begin{bmatrix} | & | & | & | \\ V1 & V2 & V_3 ...... & V_{N_t} \\ | & | & | & | \end{bmatrix} \approx \begin{bmatrix} | & | & | & | \\ W1 & W2 & W_3 ...... & W_{N_z} \\ | & | & | & | \end{bmatrix} \begin{bmatrix} h_1^T \\ h_2^T \\ h_3^T \\ . \\ h_{N_z}^T \end{bmatrix}$$

$$V \approx W_1 h_1^T + W_2 h_2^T + W_3 h_3^T + ... + W_{N_z} h_{N_z}^T \tag{3}$$

The application of NMF on noisy speech can be seen in **Figure 4**.

2.2 Optimization formulation

To estimate the basis matrix **W** and the activation matrix **H** for a given input data matrix **V**, NMF algorithm is formulated as an optimization problem. This is written as:

$$\underset{\mathrm{W,\,H}}{argmin}\, D(V|\mathrm{WH})$$

$$W \geq 0, H \geq 0 \tag{4}$$

where $D(V|\mathrm{WH})$ is an appropriately defined cost function between **V** and **W H** and the inequalities $\geq$ are element-wise. It is also common to add additional equality constraints to require the columns of **W** to sum to one, which we enforce. When $D(V|\mathrm{WH})$ is additively separable, the cost function can be reduced to

$$D(V|\mathrm{WH}) = \sum_{f=1}^{N_f} \sum_{t=1}^{N_t} d\left(V_{ft}\middle|[\mathrm{WH}]_{ft}\right) \tag{5}$$

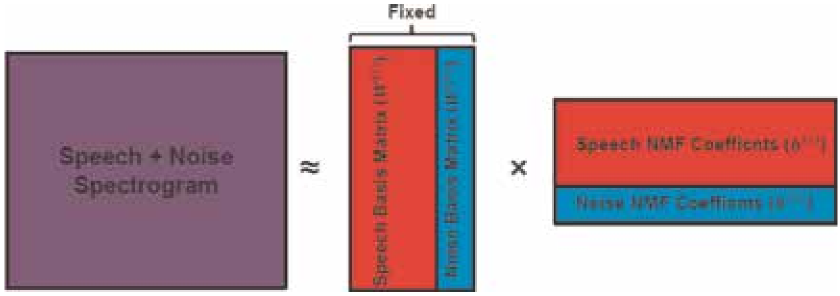

Figure 4.
Applying NMF on noisy speech.

where $[]_{ft}$ indicates its argument at row f and column t and $D(V|\mathrm{WH})$ is a scalar cost function measured between V and WH.

Popular cost functions include the Euclidean distance metric, Kullback-Liebler (KL) divergence, and Itakura-Saito (IS) divergence. Both the KL and IS divergences have been found to be well suited for audio purposes. In this work, we focus on the case where $d(q|p)$ is generalized (non-normalized) KL divergence:

$$d_{KL}(q|p) = q\, ln\frac{q}{p} - q + p \tag{6}$$

where $[]_{ft}$ indicates its argument at row f and column t and $d(q|p)$ is a scalar cost function measured between q and p.

This results in the following optimization formulation:

$$\underset{\mathrm{W,\,H}}{argmin} \sum_{f=1}^{N_f} \sum_{t=1}^{N_t} -V_{ft} \ln \left|[\mathrm{WH}]_{ft} + \right|[\mathrm{WH}]_{ft} + const$$

Subject to

$$W \geq 0, H \geq 0 \tag{7}$$

Given this formulation, we notice that the problem is not convex in **W** and **H**, limiting our ability to find a globally optimal solution to Eq. (7). It is, however, biconvex or independently convex in **W** for a fixed value of **H** and convex in **H** for a fixed value of **W**, motivating the use of iterative numerical methods to estimate locally optimal values of **W** and **H**.

2.3 Parameter estimation

To solve Eq. (7), we must use an iterative numerical optimization technique and hope to find a locally optimal solution. Gradient descent methods are the most common and straightforward for this purpose but typically are slow to converge. Other methods such as Newton's method, interior-point methods, conjugate gradient methods, and similar [4] can converge faster but are typically much more complicated to implement, motivating alternative approaches.

The most popular alternative that has been proposed is by Lee and Seung [1, 5] and consists of a fast, simple, and efficient multiplicative gradient descent-based optimization procedure. The method works by breaking down the larger optimization problem into two subproblems and iteratively optimizes over **W** and then **H**, back and forth, given an initial feasible solution. The approach monotonically decreases the optimization objective for both the KL divergence and Euclidean cost functions and converges to a local stationary point.

The approach is justified using the machinery of majorization-minimization (MM) algorithms [6]. MM algorithms are closely related to expectation maximization (EM) algorithms. In general, MM algorithms operate by approximating an optimization objective with a lower bound auxiliary function. The lower bound is then maximized instead of the original function, which is usually more difficult to optimize.

Algorithm 1 shows the complete iterative numerical optimization procedure applied to Eq. (7) with the KL divergence, where the division is element-wise, $\otimes$ is an element-wise multiplication, and 1 is a vector or matrix of ones with appropriately defined dimensions [5].

Algorithm 1 KL-NMF parameter estimation

Procedure KL-NMF ($V \in R_{+}^{N_f \times N_t}$//input data matrix.
N_z//number of basic vectors.
)
Initialize: $W \in R_{+}^{N_f \times N_z}$, $H \in R_{+}^{N_z \times N_t.}$
repeat
Optimize over **W**

$$W \leftarrow W \otimes \frac{\left(\frac{V}{\mathrm{WH}}\right)H^T}{1H^T} \tag{8}$$

Optimize over **H**

$$H \leftarrow H \otimes \frac{W^T\left(\frac{V}{\mathrm{WH}}\right)}{W^T 1} \tag{9}$$

until convergence
return: **W** and **H**

NMF is an optimization technique using EM algorithm in terms of matrix, whereas probabilistic latent component analysis (PLCA) is also an optimization technique using EM algorithm in terms of probability. In PLCA, we are going to incorporate probabilities of time and frequency. In the next section, the development of PLCA-based algorithm to incorporate time-frequency constraints is discussed.

3. A probabilistic latent variable model with time-frequency constraints

Considering this approach, we now develop a new PLCA-based algorithm to incorporate the time-frequency user-annotations. For clarity, we restate the form of the symmetric two-dimensional PLCA model we use:

$$p(f, t) = \sum_z p(z)p(f|z)p(t|z) \tag{10}$$

Compared to a modified NMF formulation, incorporating optimization constraints as a function of time, frequency, and sound source into the factorized PLCA model is particularly interesting and motivating to our focus.

Incorporating prior information into this model, and PLCA in general, can be done in several ways. The most commonly used methods are by direct observations (i.e., setting probabilities to zero, one, etc.) or by incorporating Bayesian prior probabilities on model parameters. Direct observations do not give us enough control, so we consider incorporating Bayesian prior probabilities. For the case of Eq. (10), this would result in independently modifying the factor terms $p(f|z)$, $p(t|z)$, or $p(z)$. Common prior probability distributions used for this purpose include Dirichlet priors [7], gamma priors [8], and others.

Given that we would like to incorporate the user-annotations as a function of time, frequency, and sound source, however, we notice that this is not easily accomplished using standard priors. This is because the model is factorized, and each factor is only a function of one variable and (possibly) conditioned by another, making it difficult to construct a set of prior probabilities that, when jointly applied to $p(f|z)$, $p(t|z)$, and/or $p(z)$, would encourage or discourage one source or another to explain a given time-frequency point. We can see this more clearly when we consider PLCA to be the following simplified estimation problem:

$$X(f,t) \approx \varphi(z)\varphi(f,z)\varphi(t,z) \tag{11}$$

where $X(f,t)$ is the observed data that we model as the product of three distinct functions or factors $\varphi(z)$, $\varphi(f,z)$, and $\varphi(t,z)$. Note, each factor has different input arguments and each factor has different parameters that we wish to estimate via EM. Also, forget for the moment that the factors must be normalized probabilities.

Given this model, if we wish to incorporate additional information, we could independently modify:

- $\varphi(z)$ to incorporate past knowledge of the variable z
- $\varphi(f,z)$ to incorporate past knowledge of the variable f and z
- $\varphi(t,z)$ to incorporate past knowledge of the variable t and z

This way of manipulation allows us to maintain our factorized form and can be thought of as prior-based regularization. If we would like to incorporate additional information/regularization that is a function of all three variables *z, f, and t,* then we must do something else. The first option would be to try to simultaneously modify all factors together to impose regularization that is a function of all three variables. This is unfortunately very difficult—both conceptually difficult to construct and practically difficult to algorithmically solve.

This motivates the use of posterior regularization (PR). PR provides us with an algorithmic mechanism via EM to incorporate constraints that are complementary to prior-based regularization. Instead of modifying the individual factors of our model as we saw before, we directly modify the posterior distribution of our model. The posterior distribution of our model, very loosely speaking, is a function of all random variables of our model. It is natively computed within each E step of EM and is required to iteratively improve the estimates of our model parameters. In this example, the posterior distribution would be akin to $\varphi(z,f,t)$, which is a function of t, f, and z, as required. We now formally discuss PR below, beginning with a general discussion and concluding with the specific form of PR we employ within our approach.

3.1 Posterior regularization

The framework of posterior regularization, first introduced by Graca, Ganchev, and Taskar [9, 10], is a relatively new mechanism for injecting rich, typically data-dependent constraints into latent variable models using the EM algorithm. In contrast to standard Bayesian prior-based regularization, which applies constraints to the model parameters of a latent variable model in the maximization step of EM, posterior regularization applies constraints to the posterior distribution (distribution over the latent variables, conditioned on everything else) computation in the expectation step of EM. The method has found success in many natural language processing tasks, such as statistical word alignment, part-of-speech tagging, and similar tasks that involve latent variable models.

In this case, what we do is constrain the distribution q in some way when we maximize the auxiliary bound $F(q,\Theta)$ with respect to q in the expectation step of an EM algorithm, resulting in

$$q^{n+1} = \underset{q}{argmin}\, KL(q\|p) + \Omega(q) \tag{12}$$

where $\Omega(q)$ constrains the possible space of q.

Note, the only difference between Eq. (12) and our past discussion on EM is the added term $\Omega(q)$. If $\Omega(q)$ is set to zero, we get back the original formulation and easily solve the optimization by setting q = p without any computation (except computing the posterior p). Also note to denote the use of constraints in this context, the term "weakly supervised" was introduced by Graca [11] and is similarly adopted here.

This method of regularization is in contrast to prior-based regularization, where the modified maximization step would be

$$\Theta^{n+1} = \underset{\Theta}{argmax}\, F\left(q^{n+1}, \Theta\right) + \Omega(\Theta) \tag{13}$$

where $\Omega(\Theta)$ constrains the model parameter Θ.

3.2 Linear grouping expectation constraints

Given the general framework of posterior regularization, we need to define a meaningful penalty $\Omega(q)$ for which we map our annotations. We do this by mapping the annotation matrices to linear grouping constraints on the latent variable z. To do so, we first notice that Eq. (12) decouples for each time-frequency point for our specific model. Because of this, we can independently solve Eq. (12) for each time-frequency point, making the optimization much simpler. When we rewrite our E step optimization using vector notation, we get

$$\underset{q}{argmin} -q_{ft}^T ln p_{ft} + q_{ft}^T ln q_{ft}$$

subject to

$$q_{ft}^T 1 = 1, q_{ft} \geq 0 \tag{14}$$

where q and $p(z|f,t)$ for a given value of f and t is written as q_{ft} and p_{ft} without any modification; we note q is optimal when equal to $p(z|f,t)$ as before.

We then apply our linear grouping constraints independently for each time-frequency point:

$$\underset{q}{argmin} -q_{ft}^T ln p_{ft} + q_{ft}^T ln q_{ft} + q_{ft}^T \lambda_{ft}$$

Subject to

$$q_{ft}^T 1 = 1, q_{ft} \geq 0, \tag{15}$$

where we define $\lambda_{ft} = \left[\Lambda_{ft1} \ldots\ldots \Lambda_{ft1} \Lambda_{ft2} \ldots\ldots \Lambda_{ft2}\right]^T \in R^{N_z}$ as the vector of user-defined penalty weights, T is a matrix transpose, $\geq$ is element-wise greater than or equal to, and **1** is a column vector of ones. In this case, positive-valued penalties are used to decrease the probability of a given source, while negative-valued coefficients are used to increase the probability of a given source. Note the penalty weights imposed on the group of values of z that correspond to a given source s are identical, linear with respect to the z variables, and applied in the E step of EM, hence the name "linear grouping expectation constraints."

To solve the above optimization problem for a given time-frequency point, we form the Lagrangian

$$L\left(q_{ft}, \gamma\right) = -q_{ft}^T \ln p_{ft} + q_{ft}^T \ln q_{ft} + q_{ft}^T \lambda_{ft} + \gamma\left(1 - q_{ft}^T 1\right) \tag{16}$$

With γ being a Lagrange multiplier, take the gradient with respect to q and γ:

$$\nabla_{q_{ft}} L\left(q_{ft}, \gamma\right) = -\ln p_{ft} + 1 + \ln q_{ft} + \lambda_{ft} - \gamma 1 = 0 \tag{17}$$

$$\nabla_a L\left(q_{ft}, \gamma\right) = \left(1 - q_{ft}^T 1\right) = 0 \tag{18}$$

set Eqs. (17) and (18) equal to zero, and solve for q_{ft}, resulting in

$$q_{ft} = \frac{P_{ft} \otimes exp\ (-\lambda_{ft})}{P_{ft}^T\, exp\ (-\lambda_{ft})} \tag{19}$$

where exp{} is an element-wise exponential function.

Notice the result is computed in closed form and does not require any iterative optimization scheme as may be required in the general posterior regularization framework [9], minimizing the computational cost when incorporating the constraints. Also note, however, that this optimization must be solved for each time-frequency point of our spectrogram data for each E step iteration of our final EM parameter estimation algorithm.

3.3 Parameter estimation

Now knowing the posterior-regularized expectation step optimization, we can derive a complete EM algorithm for a posterior-regularized two-dimensional PLCA model (PR-PLCA):

$$p(z|f,t) \leftarrow \frac{p(z)p(f|z)p(t|z)\overline{\Lambda}_{ftz}}{\sum_{z'} p(z')p(f|z')p(t|z')\overline{\Lambda}_{ftz'}} \tag{20}$$

where $\overline{\Lambda} = \exp\{-\Lambda\}$. The entire algorithm is outlined in Algorithm 2. Notice we continue to maintain closed-form E and M steps, allowing us to optimize further and draw connections to multiplicative nonnegative matrix factorization algorithms.

Algorithm 2 PR-PLCA with linear grouping expectation constraints

---

Procedure PLCA (
$V \in R_+^{N_f \times N_t}$ //observed normalized data
N_z//number of basis vectors
N_s//number of sources
$\Lambda \in R^{N_f \times N_t \times N_z}$//penalties
)
Initialize: feasible $p(z)$,$p(f|z)$ and $p(t|z)$

Precompute: $$\overline{\Lambda} \leftarrow \exp(-\Lambda) \tag{21}$$

repeat
Expectation step
for all z, f, t **do**

$$p(z|f,t) \leftarrow \frac{p(z)p(f|z)p(t|z)\overline{\Lambda}_{ftz}}{\sum_{z'} p(z')p(f|z')p(t|z')\overline{\Lambda}_{ftz'}} \tag{22}$$

end for
Maximization step
for all z, f, t **do**

$$p(f|z) = \frac{\sum_t V_{ft} p(z|f,t)}{\sum_{f'} \sum_{t'} V_{f't'} p(z|f',t')} \tag{23}$$

$$p(t|z) = \frac{\sum_f V_{ft} p(z|f,t)}{\sum_{f'} \sum_{t'} V_{f't'} p(z|f',t')} \tag{24}$$

$$p(z) = \frac{\sum_f \sum_t V_{ft} p(z|f,t)}{\sum_{z'} \sum_{f'} \sum_{t'} V_{f't'} p(z|f',t')} \tag{25}$$

end for
until convergence
return: $p(f|z)$, $p(t|z)$, $p(z)$ and $p(z|f,t)$

- ***Multiplicative Update Equations***

We can rearrange the expressions in Algorithm 2 and convert to a multiplicative form following similar methodology to Smaragdis and Raj [12].

Rearranging the expectation and maximization steps, in conjunction with Bayes' rule, and

$$Z(f,t) = \sum_z p(z)p(f|z)p(t|z)\overline{\Lambda}_{ftz},$$

we get

$$p(z|f,t) = \frac{p(f|z)p(t,z)\overline{\Lambda}_{ftz}}{Z(f,t)} \tag{26}$$

$$p(t,z) = \sum_f V_{ft} q(z|f,t) \tag{27}$$

$$p(f|z) = \frac{\sum_t V_{ft} q(z|f,t)}{\sum_t p(t,z)} \tag{28}$$

$$p(z) = \sum_t p(t,z) \tag{29}$$

Rearranging further, we get

$$p(f|z) = \frac{p(f|z) \sum_t \frac{V_{ft}\overline{\Lambda}_{ftz}}{Z(f,t)} p(t,z)}{\sum_t p(t,z)} \tag{30}$$

$$p(t,z) = p(t,z) \sum_f p(f|z) \frac{V_{ft}\overline{\Lambda}_{ftz}}{Z(f,t)} \tag{31}$$

which fully specifies the iterative updates. By putting Eqs. (30) and (31) in matrix notation, we specify the multiplicative form of the proposed method in Algorithm 3.

Algorithm 3. PR-PLCA with linear grouping expectation constraints in matrix notation

---

Procedure PLCA (
$V \in R_+^{N_f \times N_t}$//observed normalized data
N_z//number of basis vectors
N_s//number of sources
$\Lambda_s \in R^{N_f \times N_t}, \forall \in \{1, \ldots. N_s\}$//penalties
)
Initialize: $W \in R_+^{N_f \times N_z}, H \in R_+^{N_z \times N_t}$
Precompute:
For all s **do**

$$\overline{\Lambda}_s \leftarrow \exp\{-\Lambda_s\} \tag{32}$$

$$X_s \leftarrow V \otimes \overline{\Lambda}_s \tag{33}$$

End for
Repeat

$$\Gamma \leftarrow \sum_s (W_s H_s) \otimes \overline{\Lambda}_s \tag{34}$$

For all s **do**

$$Z_s \leftarrow \frac{X_s}{\Gamma} \tag{35}$$

$$W_{(s)} \leftarrow W_s \otimes \frac{Z_s H_s^T}{1 H_s^T} \tag{36}$$

$$H_{(s)} \leftarrow H_s \otimes \left(W_s^T Z_s\right) \tag{37}$$

End for
until convergence
return: **W** and **H**

---

4. An iterative posterior NMF method for speech enhancement in the presence of additive Gaussian noise (proposed algorithm)

Over the past several years, research has been carried out in single-channel sound source separation methods. This problem is motivated by speech denoising, speech enhancement [13], music transcription [14], audio-based forensic, and music remixing. One of the most effective approach is nonnegative matrix factorization (NMF) [5]. The user-annotations can be used to obtain the PR terms [15]. If the number of sources is more, then it is difficult to identify sources in the spectrogram. In such cases, the user interaction-based constraint approaches are inefficient.

In order to avoid the previous problem, in the proposed method, an automatic iterative procedure is introduced. The spectral components of speech and noise are modeled as Gamma and Rayleigh, respectively [16].

4.1 Notation and basic concepts

Let noisy speech signal x[n] be the sum of clean speech s[n] and noise d[n] and their corresponding magnitude spectrogram be represented as

$$|\boldsymbol{X}(\boldsymbol{f},\boldsymbol{t})| = |\boldsymbol{S}(\boldsymbol{f},\boldsymbol{t})| + |\boldsymbol{D}(\boldsymbol{f},\boldsymbol{t})| \tag{38}$$

where f represents the frequency bin and t the frame number. The observed magnitudes in time-frequency are arranged in a matrix $\mathbf{X} \in R_{+}^{f\times t}$ of nonnegative elements. The source separation algorithms based on NMF pursue the factorization of $\mathbf{X}$ as a product of two nonnegative matrices, $\boldsymbol{W} = [\boldsymbol{w}_1, \boldsymbol{w}_2, \dots, \boldsymbol{w}_R] \in R_{+}^{f\times R}$ in which the columns collect the basis vectors and $\boldsymbol{H} = \left[h_1^T, h_2^T, \dots, h_R^T\right]^T \in R_{+}^{R\times t}$ that collects their respective weights, i.e.,

$$X = \mathrm{WH} = \sum_{z=1}^{R} W_z H_z \tag{39}$$

where R denotes the number of latent components.

4.2 Proposed regularization

There are several ways to incorporate the user-annotations into latent variable models, for instance, by using the suitable regularization functions. For expectation maximization (EM) algorithms, posterior regularization was introduced by [9, 11]. This method is data dependent. This method gives richness and also gives the constraints on the posterior distributions of latent variable models. The applications of this method is used in many natural language processing tasks like statistical word alignment, part-of-speech tagging. The main idea is to constrain on the distribution of posterior, when computing expectation step in EM algorithm.

The prior distributions for the magnitude of the noise spectral components are modeled as Rayleigh probability density function (PDF) with scale parameter σ, which is fitted to the observations by a maximum likelihood procedure [16, 17], i.e.,

$$f(x;\sigma) = \frac{x}{\sigma^2} e^{-x^2/2\sigma^2}\, for\ x \geq 0\ with\ \sigma^2 = \frac{1}{2N}\sum_{i=1}^{N} x_i^2 \tag{40}$$

The above equation can be written as

$$f(x;\sigma) = e^{\log\left(\frac{x}{\sigma^2}\right)} e^{-x^2/2\sigma^2} = e^{\log\left(\frac{x}{\sigma^2}\right) - \frac{x^2}{2\sigma^2}} \tag{41}$$

By applying negative logarithm on both sides of (41), we will get

$$-\log\left(f(x;\sigma)\right) = -\log\left(e^{\log\left(\frac{x}{\sigma^2}\right) - \frac{x^2}{2\sigma^2}}\right) = \frac{x^2}{2\sigma^2} - \log\left(\frac{x}{\sigma^2}\right) \tag{42}$$

Then, the regularization term for the noise is defined as

$$\Lambda_N \equiv \Lambda_{S_1} = -\log f(x;\sigma) = \frac{x^2}{2\sigma^2} - \log\frac{x}{\sigma^2}. \tag{43}$$

The spectral components of speech modeled as Gamma probability density function [16, 18]

$$f(x;k,\theta)=\frac{x^{k-1}e^{\frac{-x}{\theta}}}{\theta^{k}\Gamma(k)} \tag{44}$$

with shape parameter $k>0$ and scale parameter $\theta>0$:

$$\theta=\frac{1}{kN}\sum_{i=1}^{N}x_i \text{ and } k\approx\frac{3-s+\sqrt{(s-3)^2+24s}}{12s} \tag{45}$$

where the auxiliary variable s is defined as $s=\ln\left(\frac{1}{N}\sum_{i=1}^{N}x_i\right)-\frac{1}{N}\sum_{i=1}^{N}\ln(x_i)$.

The regularization term for the speech samples is defined as (by applying negative logarithm in both sides of (44))

$$\Lambda_{SP}\equiv\Lambda_{S_2}=-\log f(x;k,\theta)=\frac{x}{\theta}-\log\left(\frac{x^{k-1}}{\theta^{k}\Gamma(k)}\right),x\geq 0 \tag{46}$$

Special case: When we fix $k=1$, the Gamma density simplifies to the exponential density and

$$f(x;1,\theta)=\frac{1}{\theta}e^{\frac{-x}{\theta}},\Lambda_{SP}\equiv\Lambda_{S_2}=\frac{x}{\theta},x\geq 0 \tag{47}$$

The proposed multiplicative nonnegative matrix factorization method is summarized in Algorithm 4 [16]. In general, like in the specific case of Algorithm 4, one can only guarantee the monotonous descent of the iteration through a majorization-minimization approach [19] or the convergence to a stationary point [20].

The subscript(s) with parenthesis represents corresponding columns or rows of the matrix assigned to a given source. **1** is an approximately sized matrices of ones, and $\otimes$ represents element-wise multiplication.

Algorithm 4: Gamma-Rayleigh regularized PLCA method (GR-NMF)

Procedure

$X\in R_{+}^{f\times t}$ % Observed normalized data

$\Lambda_S\in R_{+}^{f\times t}, s\in\{1,.....,N_S\}$ % Λ_S-Penalties, N_S-Number of sources

$$\Lambda_{s(NEW)}=0$$

$$\Lambda_{S_1}=\Lambda_{N(OLD)}=\frac{X^2}{2\sigma^2}-\log\frac{X}{\sigma^2} \text{ and } \Lambda_{S_2}=\Lambda_{SP(OLD)}=\frac{X}{\theta}-\log\left(\frac{X^{k-1}}{\theta^{k}\Gamma(k)}\right) \tag{48}$$

$$\widetilde{\Lambda}_{s(OLD)}\leftarrow\exp\{-\Lambda_s\} \tag{49}$$

Repeat

For all s do

$$\widetilde{\Lambda}_s=(1-\mu)\Lambda_{s(OLD)}+\mu\Lambda_{s(NEW)} \text{ \%Update penalties using LMS} \tag{50}$$

$$\Lambda_{s(OLD)}=\Lambda_{s(NEW)} \tag{51}$$

$$X_s \leftarrow X \otimes \widetilde{\Lambda}_S \tag{52}$$

End for

$$\Gamma \leftarrow \sum_s \left(W_{(s)} H_{(s)}\right) \otimes \widetilde{\Lambda}_S \tag{53}$$

$$Z_s \leftarrow \frac{X_s}{\Gamma} \tag{54}$$

For all s do

$$W_{(s)} \leftarrow W_{(s)} \otimes \frac{Z_s H_{(s)}^T}{1\mathrm{H}_{(s)}^T} \tag{55}$$

$$H_{(s)} \leftarrow H_{(s)} \otimes \left(W_{(s)}^T Z_s\right) \tag{56}$$

End for

Reconstruction

For all s do

$$M_s \leftarrow \frac{W_{(s)} H_{(s)}}{\mathrm{WH}} \ \ \%\ \mathit{Compute\ Filter} \tag{57}$$

$$\hat{X}_s \leftarrow M_s \otimes X\ \%\ \mathit{Filter\ Mixture} \tag{58}$$

$$x_s \leftarrow \mathit{ISTFT}\left(\hat{X}_s, \angle\mathrm{X}, P\right)\ \ \%\ P - \ \mathit{STFT\ parameters} \tag{59}$$

if update k % Gamma model

$$s = \ln\left(\frac{1}{N}\sum \hat{X}_s\right) - \frac{1}{N}\sum \ln\left(\hat{X}_s\right), k \approx \frac{3 - s + \sqrt{(s-3)^2 + 24s}}{12s} \tag{60}$$

else % Exponential model

k = 1,

end

$$\theta = \frac{1}{kN}\sum \hat{X}_s \tag{61}$$

$$\Lambda_{S_1} = \Lambda_{N(OLD)} = \frac{\hat{X}_{s_1}^2}{2\sigma^2} - \log\frac{\hat{X}_{s_1}}{\sigma^2}$$

$$\Lambda_{S_2} = \Lambda_{SP(OLD)} = \frac{\hat{X}_{s_2}}{\theta} - \log\left(\frac{\hat{X}_{s_2}^{\mathrm{k}-1}}{\theta^k \Gamma(k)}\right) \tag{62}$$

$$\Lambda_{s(NEW)} = \exp\left(-\Lambda_{s(OLD)}\right)\ \ \%\ \ \Lambda_{s(OLD)} \text{ represents both } \Lambda_{SP} \text{ and } \Lambda_N \tag{63}$$

End for

Until Convergence

Return: Time domain signals x_s

5. Experimental results

The speech and noise audio samples were taken from NOIZEUS [21]. Sampling frequency is 8 KHz. The algorithm is iterated until convergence [16]. The proposed method was compared with Euclidean NMF (EUC-NMF) [5], Itakura-Saito NMF (IS-NMF) [22], posterior regularization NMF (PR-NMF) [15], Wiener filtering [23], and constrained version of NMF (CNMF)[24]. These methods are implemented by considering nonstationary noise, babble noise and street noise. The performance of proposed method was evaluated by using perceptual evaluation of speech quality (PESQ) [25] and source-to-distortion ratio (SDR) [26]. SDR gives the average quality of separation on dB scale and considers signal distortion as well as noise distortion. For PESQ and SDR, the higher value indicates the better performance. **Tables 1** and **2** show the PESQ and SDR values of different NMF algorithms evaluated. The experimental results show that proposed method performs better than other existing methods in terms of the PESQ and SDR indices.

Input SNR	Evaluation	Wiener [22]	IS-NMF [21]	EUC-NMF [5]	CNMF [23]	PR-NMF [15]	Proposed GR-NMF (k=1)	Proposed GR-NMF (updated k)
0 dB	PESQ	1.50	1.71	1.62	1.40	1.79	1.67	1.92
	SDR	1.03	1.43	1.78	1.53	3.73	9.41	8..98
5 dB	PESQ	2.01	2.18	2.03	1.97	2.21	2.26	2.36
	SDR	4.89	5.26	7.17	6.73	8.28	13.04	13.51
10 dB	PESQ	2.31	2.37	2.42	2.39	2.45	2.62	2.59
	SDR	8.42	8.98	8.58	9.12	9.57	16.01	16.55
15 dB	PESQ	2.52	2.50	2.54	2.63	2.68	3.05	2.75
	SDR	9.65	9.97	10.7	9.74	10.4	18.52	19.23

Table 1.
PESQ and SDR for babble noise.

Input SNR	Evaluation	Wiener [22]	IS-NMF [21]	EUC-NMF [5]	CNMF [23]	PR-NMF [15]	Proposed GR-NMF (k=1)	Proposed GR-NMF (updated k
0 dB	PESQ	1.40	1.62	1.55	1.31	1.72	2.09	1.89
	SDR	3.31	3.72	3.86	3.51	5.73	9.02	9.18
5 dB	PESQ	1.92	2.03	1.94	1.89	2.16	2.37	2.31
	SDR	6.59	6.86	8.19	7.03	9.78	15.85	15.76
10 dB	PESQ	2.37	2.45	2.42	2.51	2.59	2.73	2.65
	SDR	10.21	11.73	12.83	12.52	13.18	19.97	20.57
15 dB	PESQ	2.58	2.63	2.67	2.72	2.79	2.95	2.89
	SDR	13.39	14.5	13.3	14.92	16.2	22.14	23.84

Table 2.
PESQ and SDR for street noise.

6. Conclusion

A novel speech enhancement method based on an iterative and regularized NMF algorithm for single-channel source separation is proposed. The clean speech and noise magnitude spectra are modeled as Gamma and Rayleigh distributions, respectively. The corresponding log-likelihood functions are used as penalties to regularize the cost function of the NMF. The estimation of basis matrices and excitation matrices are calculated by using proposed regularization of multiplicative update rules. The experiments reveal that the proposed speech enhancement method outperforms other existing benchmark methods in terms of SDR and PESQ values.

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Chapter 4

A Self-Paced Two-State Mental Task-Based Brain-Computer Interface with Few EEG Channels

Farhad Faradji, Rabab K. Ward and Gary E. Birch

Abstract

A self-paced brain-computer interface (BCI) system that is activated by mental tasks is introduced. The BCI's output has two operational states, the active state and the inactive state, and is activated by designated mental tasks performed by the user. The BCI could be operated using several EEG brain electrodes (channels) or only few (i.e., five or seven channels) at a small loss in performance. The performance is evaluated on a dataset we have collected from four subjects while performing one of the four different mental tasks. The dataset contains the signals of 29 EEG electrodes distributed over the scalp. The five and seven highly discriminatory channels are selected using two different methods proposed in the paper. The signal processing structure of the interface is computationally simple. The features used are the scalar autoregressive coefficients. Classification is based on the quadratic discriminant analysis. Model selection and testing procedures are accomplished via cross-validation. The results are highly promising in terms of the rates of false and true positives. The false-positive rates reach zero, while the true-positive rates are sufficiently high, i.e., 54.60 and 59.98% for the 5-channel and 7-channel systems, respectively.

Keywords: brain-computer interface, mental task, self-paced, autoregressive modeling, quadratic discriminant analysis

1. Introduction

Brain-computer interfaces (BCIs) aim at providing an alternative means of communication for motor-disabled people suffering from diseases such as brain injury, brainstem stroke, high-level spinal cord injury (SCI), amyotrophic lateral sclerosis (ALS, also known as Maladie de Charcot or Lou Gehrig's disease), muscular dystrophies, multiple sclerosis (MS), cerebral palsy (CP), or locked-in syndrome (sometimes called ventral pontine syndrome, cerebromedullospinal disconnection, pseudocoma, and de-efferented state). Well-developed BCI systems are used by motor-disabled people to control their environment. They can also be used by healthy individuals for entertainment purposes such as playing computer games.

Existing BCI systems are categorized in two major classes: system-paced (or synchronous) and self-paced (or asynchronous). In system-paced BCIs, the user can only control the BCI during specific time intervals that are predefined by the system and not by the user. A self-paced BCI, on the other hand, can be available for control by the user at all times. It is clear that the second class is better and more efficient in terms of practicality and applicability to real-life applications.

Two types of states (or modes) are usually assumed for the output of a self-paced BCI: the no-control (NC) state and the intentional control (IC) state. This type of BCIs is in the NC mode most of the time. However, when the user issues a mental command that would lead, for example, to switching the light on, moving the computer cursor to the right, etc., the system changes its state from the NC mode to the IC mode. After that, the BCI returns to the NC state.

Two measures that can properly evaluate the performance of a self-paced BCI are the true-positive rate (TPR) and the false-positive rate (FPR). A true-positive outcome results from correctly classifying a command as an IC state, and a false-positive outcome results from the BCI misclassifying a no control as an IC state. The ratios of true positives and false positives to the total number of classifications yield the TPR and FPR, respectively. Further details on BCIs can be found in [1–5].

Due to the high false activation rates, BCI systems are deemed unsuccessful for use in real-life applications. This is because false activations are a major cause of user frustration. To further illustrate this point, suppose that the output rate of a self-paced BCI is 5 Hz (i.e., five outputs/s, as in the BCI designed in this paper) and the FPR value is 1%. This FPR of 1% means one false positive in every 100 outputs of the BCI. As the BCI generates 100 outputs in 20 s, there would be three false activations in every minute, which is too high for practical purposes. Considering the fact that a self-paced BCI is in the no-control mode for most of the time, even a low FPR would greatly annoy and frustrate any user. This is why for BCI systems, lowering the FPR is of extreme importance.

Mental tasks are a class of neurological phenomena that can be exploited in BCI systems. They generally refer to intentional cognitive tasks that are done by the brain. Mental tasks can be mental mathematical calculations (such as multiplication and counting), mental rotation of a two- or three-dimensional object, motor imagery, visualization, etc.

Motor imagery is a task that has been investigated by a large majority of BCI studies [6–64]. The use of other types of mental tasks in BCI studies has received little attention in the literature. The papers that have studied non-motor imagery mental tasks along with the motor imagery tasks include [65–84]. Studies [85–96] have only considered non-motor imagery mental tasks.

The mental tasks investigated in [65] are motor imagery of opening and closing of the users' hand(s) and serially subtracting seven from a large number. In [66], four motor imagery tasks of (the users) left hand movement, right hand movement, foot movement, and tongue movement along with a simple calculation task (i.e., repeated subtraction of a constant number from a randomly chosen number) are considered as the mental tasks. The mental tasks used in [67] are the imagination of left and right hand movements, cube rotation, and subtraction. Four imagery tasks, i.e., spatial navigation around a familiar environment, auditory imagery of a familiar tune, and right and left motor imageries of opening and closing the hand, are investigated in [68]. In [69, 70], the imagination of left and right hand (or arm) movements, cube rotation, subtraction, and word association are studied. In [71, 72, 75–77, 79, 81], the imagination of repetitive self-paced left or right hand movement and the generation of words beginning with the same random letter are investigated. The EEG data used in these studies are those provided by the IDIAP Research Institute in Switzerland [70]. The studies in [77, 81] consider the imagination of the left or right hand movement as well using the data collected by the BCI laboratory at Graz University of Technology in Austria [16]. In [73], the mental tasks are auditory recall, mental navigation, sensorimotor attention of the left hand, sensorimotor attention of the right hand, mental calculation, imaginary movement of the left hand, and imaginary movement of the right hand. The mental tasks used in [74] are the exact calculation of repetitive additions, imagination of left finger movement, mental rotation of a cube, and evocation of a nonverbal audio signal. In [78], the right and left hand extension motor imageries, subtraction, navigation imagery, auditory imagery, phone imagery, and idle task are investigated. The mental tasks considered in [80] include the right and left hand flexion motor imageries, subtraction, navigation imagery, auditory imagery, phone imagery, and idle task. The mental tasks considered in [82] are subtraction, navigation imagery, auditory recall, phone imagery, and motor imageries of the left and right hands. Hand movements and word imagination are the mental tasks used in [83]. Imagination of left and right hand movements, mental rotation of a 3D geometric figure, and mental subtraction of a two-digit number from a three-digit number are considered in [84].

The old and small datasets of Keirn and Aunon [85] that contain non-motor imagery mental tasks are employed in [86–90, 92, 94–96]. Vowel speech imagery (i.e., imaginary speech of the two English vowels /a/ and /u/) is proposed as a control scheme for the BCI system in [91]. In [93], the mental arithmetic and spatial imageries are investigated. Real fist rotation and imagined reverse counting are investigated in [97].

From all BCI systems designed in these studies, only the systems in [19, 24, 32, 39, 42, 46, 57, 61, 67, 69, 70] and [76, 78, 80, 82] are self-paced. The FPR values are not reported in [57, 69, 70, 76, 78, 80, 82]. Even though the number of FPs and TPs is mentioned in [32, 46], the rates of FPs and TPs are not given.

The FPRs are given in [19, 24, 42, 61]. In [19], the given FPR values are in the 10–77% range. In [24], the BCI system was evaluated in terms of FPs during only one 3-minute interval. No FPs were generated during this interval; however, since the designed BCI is too slow, it is deemed impractical for the real-life applications. The minimum time period between two subsequent active states of the system is 4 s. In [42], the FPRs of the BCI systems are between 3.8% and 32.5%. In [61], the reported false activation rate is in the range of 0–3.25 activations/minute.

In [39], the specificity rates (i.e., 100–FPR%) are given. Based on the specificity rates, the FPR values are between 0.38 and 14.38%. Based on the confusion matrices given in [67], the FPRs are in the range of 0–9%.

The ultimate and first goal of conducting this study is to develop a self-paced two-state mental task-based BCI with a zero or near-zero false activation rate using EEG signals. The mental tasks investigated are the visualization of some words as they are written, multiplication, mentally rotating a 3D object, and motor imagery. We collected the EEG signals of these four tasks as they were being performed mentally and also during the baseline state, i.e., when the subjects were not performing any of the four mental tasks as will be explained in Section 2. The number of EEG channels used was 29. The details on each mental task and the dataset are provided in the next section where the experimental protocol is described.

The second goal is to design a BCI with few channels. Such a BCI has few electrodes to collect the EEG signals and would be significantly more efficient computationally, leading to BCIs that operate in real time. Thus, for practical applications, the number of EEG channels should be small. In Section 3.1, we discuss how we choose five or seven channels that would yield acceptable performance.

For each subject, four different BCIs are developed. Each BCI is based on one of the four mental tasks mentioned above, i.e., in each BCI, one mental task is considered as the IC task (i.e., the user is indeed issuing a command). The other three mental tasks are considered as NC tasks. The BCI system should remain in the NC mode during the NC tasks and the baseline.

Even though the system performance is evaluated off-line, the EEG signals are analyzed in a self-paced manner. A signal trial is divided into overlapping segments. Each segment is labeled as either IC or NC, depending on whether or not it belongs to the IC task. The performance of the system is then evaluated in terms of TPR and FPR.

Classification is based on the quadratic discriminant analysis due to its simplicity and accuracy. The features to be classified are the scalar autoregressive (AR) coefficients of the EEG signals. The feature extraction and the classification methods employed are efficient in terms of computational complexity. The cross-validation process is performed so as to obtain the optimal order of AR coefficients as well as the best EEG channels for every mental task of every subject.

2. Dataset

The EEG signals of four subjects were collected while they were seated in a chair approximately 75 cm in front of an LCD monitor in a 4×4 m^2 room. The subjects were asked to keep their eyes open during the recordings. Using an electrode cap, the signals were captured from 29 channels located at Fpz, AF3, AF4, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, PO3, PO4, and Oz, according to the 10–10 system [98, 99]. Electrodes were properly distributed over the scalp to study the signals of the different brain regions. Refer to **Figure 1** to see the electrode positions. The earlobes were electrically linked together and used as the reference. The EEG signals were amplified and digitized using a 12-bit analog-to-digital converter. The sampling rate was 500 Hz.

Every subject attended three recording sessions on 3 different days. They were asked to perform four mental tasks. Each session started with the preparation and setup and consisted of six recording runs. Twelve minutes of EEG signals were approximately recorded in a run. The subjects were instructed to complete the six runs one after the other at their own pace. Each run consisted of signals of 20

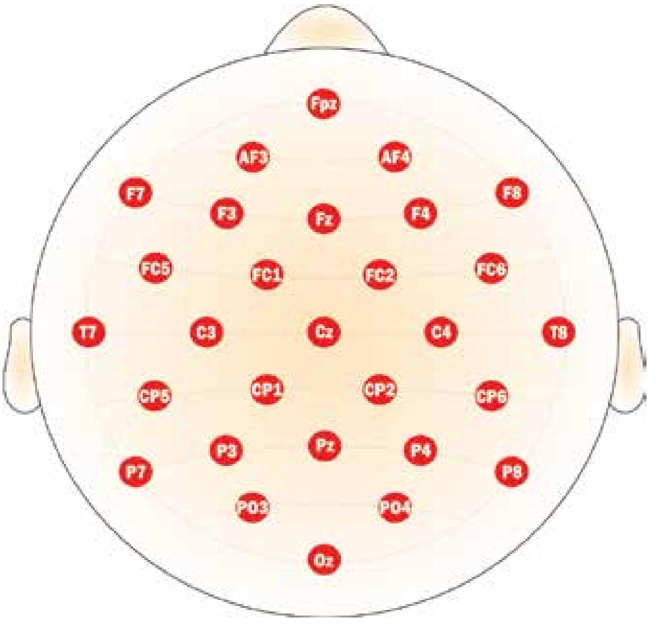

Figure 1.
EEG signals were recorded from 29 electrodes distributed over the scalp according to the 10–10 system.

epochs (i.e., five epochs for each of the four mental tasks). An epoch was 32.5 ± 2.5 s long. To avoid possible adaptation, the order of epochs belonging to different mental tasks was changed randomly from one run to the other.

The timing of the epochs was as follows. At the beginning of each epoch, there was a break with a length of 15 ± 2.5 s. The break had a variable length in different epochs so as to avoid possible adaptation. A "Start" cue was displayed after the break on the screen to prompt the subject to perform a specific mental task. The task to be performed was shown on the screen. The length of the Start cue was 4 s. The subjects had been instructed to start to perform the mental task approximately 1 s after the disappearance of the Start cue and to keep performing the task until a "Stop" cue appeared on the screen. The 1-s delay was used to avoid any possible effects of visual evoked potentials. The time interval between the Start cue and the Stop cue was 10 s. The Stop cue lasted for 2.5 s. After the Stop cue, the break of the next epoch started. **Figure 2** illustrates the timing of each epoch.

The background of the screen was always black. During the break interval of each epoch, "Break" was written on the screen in white and in a size which could be easily read from a distance of 75 cm. The name of a specific mental task written in white was the Start cue. The size of the Start cue was the same as Break. The word "STOP" written in a green circle was the Stop cue.

The mental tasks were:

1. Visualizing some words being written on a board: subjects were told to imagine a board on which they were writing their full names.

2. Non-trivial multiplication: the subjects performed multiplication of two two-digit numbers. The numbers to be multiplied were given to them as the Start cue.

3. Mentally rotating a 3D object: the subjects imagined that they were rotating a laptop mentally.

4. Motor imagery: the subjects imagined extending his/her right hand.

The subjects were asked to be in the baseline state during the break interval of each epoch, i.e., they should not be performing any of the four mental tasks of the experiment and were supposed to remain looking at the screen and not move. They should attain the same physical condition as that assumed when they performed the mental tasks.

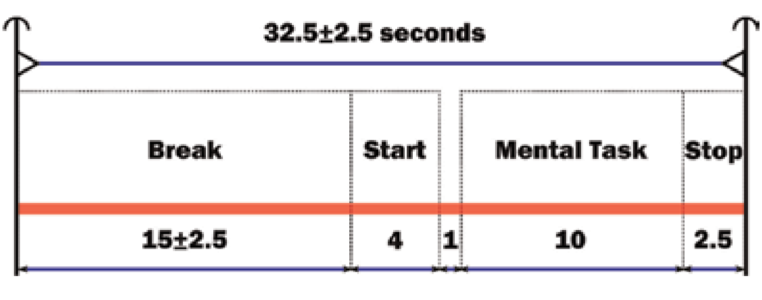

Figure 2.
Epoch timing. A "Start" cue was displayed on the screen for 4 s after a break of length of 15 ± 2.5 s. The subject was told to wait about 1 s after the cue disappeared before performing a mental task for about 10 s. The "Stop" cue was displayed on the screen for 2.5 s, informing the subject of the end of the 10-s interval. The next epoch then started.

For each of the four mental tasks, 300 s (30 10-s epochs) of EEG signals and for the baseline, about 1800 s (120 epochs) of EEG signals were recorded in each session. Therefore, at the end of the last session, we had 90 epochs of each mental task and 360 epochs of the baseline for each subject.

The experimental protocol had been approved by the Behavioral Research Ethics Board of the University of British Columbia, and all subjects signed the required consent form.

3. Methodology

3.1 EEG channel selection

The dataset is formed by the signals from 29 electrodes. However, a BCI system with 29 channels is impractical for use in real-life applications. For practical applications, the number of channels should be as small as possible. We thus select a smaller set of the channels that together yield the best performance for the final design of our system.

Suppose that we have a BCI system with n channels and we need to select the BCI that has m channels ($m < n$) and yields the best performance. The ideal but not always computationally practical way is to consider all the possible m-channel combinations of the n channels and select the combination that yields the best system performance. For instance, if we want to decrease the number of channels from 29 to 7, the system performance needs to be evaluated for all 1,560,780 different 7-channel combinations and then compared. Moreover, in order to make the results more robust, the performance evaluation of the system is usually carried out for different training and testing sets via a cross-validation process. If we assume that the number of evaluation which runs in cross-validation is 5, the number above (1,560,780) should be multiplied by 5. This forms a prohibitively large amount of computations as the processing time will take several days. It is thus impractical for implementation.

In this study, two approaches are performed for selecting the best system that has m channels. The first approach deletes the channels (from among the 29-channel system) that results in the least reduction in the performance of the remaining system. The channels are deleted one by one. The second approach builds a new system by adding channels one by one to the newly built system. A channel added to the new system is selected from the 29-channel system so that the performance of the new system is maximal. These two approaches result in two methods that we denote as MDelete and MForm. Even though these methods are not optimal as the method mentioned above (i.e., considering all possible combinations), they still reach the goal to a certain extent.

Channel selection method one: in channel selection method one (MDelete), all 29 channels are first considered. The resultant FPR and TPR values after deleting each channel are obtained. The BCI system with 28 channels that yields the best performance is selected. That is, the channel whose removal results in the best 28-channel system is detected and deleted from the list. This task is repeated on the remaining list (i.e., on 28 channels), and the best 27-channel system is found. This is repeated again until all but m channels are omitted.

Channel selection method two: channel selection method two (MForm) is similar to the first one except that it is carried in the reverse direction and the selection of the channels differs as explained below. In the first iteration, the BCI system is assumed to have one channel only. The channel with the best performance among the 29 existing channels is thus detected. This will form the best BCI that has one channel only. In the second iteration, the BCI system is assumed to have two channels only. One of these two channels is the one already selected in iteration 1. Thus the performance of each channel in the remaining 28 channels, together with the channel selected in the first iteration, is obtained. Among these 28 possibilities, the channel (together with the already selected one) that yields the best performance is selected and added to the list of the best channels. In the third iteration, three channels are considered. These are formed by each channel from the remaining list (i.e., 27 channels) and the two channels already selected in the previous iterations. The channel that together with the two already selected channels yields the 3-channel BCI system with the best performance is added to the list. This procedure is repeated until m channels are added to the list of the best channels.

3.2 Procedure

The length of each mental task epoch is 10 s. The baseline epochs have a variable length in the range of 15 $\pm$ 2.5 s. Since the sampling frequency is 500 samples/s, each mental task epoch consists of 5000 samples, and the number of samples in a baseline epoch varies between 6250 and 8750.

To process the data, every epoch is divided into overlapping segments. Each segment is of length 1 s (i.e., 500 samples) and overlaps with the previous segment by 400 samples. In other words, the BCI system generates an output every 100 samples using the last 500 samples of the signals. Since 100 samples are equivalent to 0.2 s, the output rate of the BCI is 5 Hz.

Feature selection and classification: autoregressive (AR) modeling is used to obtain the features from the segments. Based on the results in [100, 101], 1 s of the EEG signal is sufficiently long for the AR model estimation. The feature vector is formed by concatenating the AR coefficients (estimated from the segments of the selected channels) into a single vector. This vector is then fed to the classifier for classification purposes. Classification is performed using quadratic discriminant analysis. The AR modeling and quadratic discriminant analysis are briefly explained in Appendices A and B of this paper.

Custom designing: custom designing the system for every subject yields improvements in the overall BCI performance [102, 103]. In this study, the BCI system is customized for each subject and for each mental task by selecting the channels and AR orders during cross-validation.

Cross-validation: to perform the cross-validation, we randomly divide the whole set of segments into five equal-sized sections. Four of the data sections are used to train and validate the system. Testing is carried on the remaining section. The four data sections assigned to training and validation are further divided randomly into five data partitions of equal size. Four partitions are used for training and one is used for validation.

Selecting the best five and seven channels: we select the top five and also the top seven best performing channels for future processing using MDelete and MForm with the AR model order of 40. We then compare the results of the 5-channel cases with those of the 7-channel cases to figure out the final design for the BCI system. Channel selection is accomplished separately for different subjects and different mental tasks. **Tables 1** and **2** list the best channels selected using MDelete and MForm, respectively. For each subject and each mental task, each channel selected by both MDelete and MForm is shown in bold in the tables.

MDelete and MForm give BCI systems with different channel combinations. This is because each of these methods obtains a channel set which is locally optimum. The globally optimum set can be obtained by the exhaustive method

	Selected channels (from best to worst)						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Subject 1							
Sentence visualization	**T8**	**F8**	F3	AF3	**Oz**	CP6	**P7**
Non-trivial multiplication	FC5	**FC6**	PO3	T7	C4	CP6	C3
3D object rotation	**FC6**	T8	F3	AF3	CP6	AF4	F8
Motor imagery	**CP6**	**T8**	**P8**	AF3	F7	FC2	T7
Subject 2							
Sentence visualization	**P8**	**FC6**	**T7**	F3	PO4	P7	P3
Non-trivial multiplication	Oz	**Fpz**	Fz	T7	**FC6**	P3	C3
3D object rotation	**Oz**	T7	P3	FC5	Fz	**C4**	Cz
Motor imagery	CP2	**Oz**	F7	Fpz	P7	CP6	F4
Subject 3							
Sentence visualization	**PO3**	**P8**	P4	AF4	T7	**P7**	C4
Non-trivial multiplication	**Oz**	**Fpz**	Pz	T7	CP1	PO4	CP5
3D object rotation	**FC2**	CP1	PO4	P8	Cz	F4	FC6
Motor imagery	T7	**P7**	CP2	Fpz	CP6	F7	FC6
Subject 4							
Sentence visualization	**P8**	Cz	PO3	**CP5**	**T7**	PO4	AF3
Non-trivial multiplication	F4	CP5	**T8**	**P7**	**P8**	**Oz**	F3
3D object rotation	AF3	**FC5**	**AF4**	P7	**C3**	T8	PO4
Motor imagery	Cz	**P8**	P7	FC6	T7	**F3**	CP5

Table 1.
Channels selected for different subjects and mental tasks using channel selection method one (MDelete).

	Selected channels (from best to worst)						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Subject 1							
Sentence visualization	**T8**	FC5	**F8**	P4	T7	**P7**	**Oz**
Non-trivial multiplication	F7	Oz	**FC6**	T8	F8	P7	CP1
3D object rotation	T7	**FC6**	P8	CP2	P7	Oz	F4
Motor imagery	Oz	P7	C3	**CP6**	**T8**	**P8**	FC6
Subject 2							
Sentence visualization	**P8**	F7	**FC6**	**T7**	FC5	AF3	T8
Non-trivial multiplication	CP6	P4	T8	**Fpz**	C4	F7	**FC6**
3D object rotation	P7	P4	**C4**	**Oz**	FC6	AF4	F7
Motor imagery	CP5	Fz	FC6	T7	FC1	**Oz**	C4
Subject 3							
Sentence visualization	**PO3**	Oz	Fpz	**P8**	**P7**	Pz	CP1
Non-trivial multiplication	**Oz**	P8	**Fpz**	P7	Cz	T8	AF3
3D object rotation	CP5	**FC2**	P7	P4	T7	Oz	Fz
Motor imagery	T8	Oz	P3	PO3	**P7**	AF4	AF3

	Selected channels (from best to worst)						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Subject 4							
Sentence visualization	CP6	**P8**	FC5	AF4	**T7**	**CP5**	Oz
Non-trivial multiplication	AF4	F7	**T8**	**P8**	**P7**	T7	**Oz**
3D object rotation	F3	F7	**AF4**	PO3	**FC5**	Oz	**C3**
Motor imagery	CP2	P3	AF4	F8	**P8**	**F3**	F7

Table 2.
Channels selected for different subjects and mental tasks using channel selection method two (MForm).

mentioned earlier in which the best combination is selected by considering all possible combinations of channels. Finding the global optimum is computationally impossible for our application. We hence have to be satisfied with the local optima.

Finding the optimum AR model order: after selecting the best five and the best seven channels for each subject and each mental task, we find the optimum AR model order for each of these two cases in the cross-validation process. The initial AR model order is equal to 41. If the FPR for an order reaches zero, that order is selected as the optimum order; if not, the order is increased by one, and the FPR of the new order is then calculated. Increasing the AR order is terminated once the FPR is zero or a maximum order of 136 is reached. The order corresponding to the minimum FPR is chosen as the optimum AR order for the latter case.

4. Experimental results

For each subject and each mental task, there are two sets of five best channels (one is obtained using MDelete and the other is obtained using MForm). The performance of the 5-channel set that yielded the better performance is summarized in **Table 3**. For each subject and each mental task, the table shows whether the channels obtained using MDelete (1) or MForm (2) are selected. This is indicated under the channel selection method (CSM) column. It also shows the mean values of the TPR and FPR obtained from the cross-validation and testing processes in two separate rows. The optimum AR model order is also included in the table. In **Table 4**, the difference in the performance between the 5-channel BCIs using MDelete and MForm is given. **Table 5** shows the results of the t-test between any 2 of the four mental tasks for each subject in the 5-channel BCIs.

The performance of the 7-channel BCIs using the two channel selection methods are compared with each other, and the performance of the better method is given in **Table 6** for each subject and each mental task. The performance difference between the two channel selection methods is shown in **Table 7**.

In **Tables 3** and **6**, the values related to the highest performance are shown in bold, while those related to the lowest performance are underlined.

The *Welch's t*-test [104], as a statistical significance test, is performed on the TPR values for measuring the performance difference between MDelete and MForm (for each subject and each mental task) and between every pair of the four mental tasks (for each subject). The null hypothesis is that there is no difference between the TPR values of the two groups (these two groups can be the two channel selection methods or any two mental tasks). We assume a 5% significance level. The null hypothesis is rejected if the resultant p-value is less than 0.05. This means that the

Subject	Process	Visualization				Multiplication				Object rotation				Motor imagery			
		CSM	AR	TPR	FPR	CSM	AR	TPR	FPR	CSM	AR	TPR	FPR	CSM	AR	TPR	FPR
1	Validation	1	87	59.82	0.00	2	98	61.52	0.00	2	89	59.82	0.00	2	93	56.56	0.00
	Testing			57.78	0.00			61.24	0.00			59.71	0.00			55.30	0.00
2	Validation	1	91	57.37	0.00	1	90	58.29	0.00	2	84	57.23	0.00	1	90	54.68	0.00
	Testing			58.56	0.00			57.93	0.00			56.00	0.00			54.38	0.00
3	Validation	2	81	61.98	0.00	2	82	63.25	0.00	2	95	57.23	0.00	1	90	57.25	0.00
	Testing			62.68	0.00			63.72	0.00			55.37	0.00			58.51	0.00
4	Validation	1	101	55.21	0.00	1	129	42.89	0.00	1	136	33.03	0.20	1	134	41. 62	0.01
	Testing			53.89	0.00			42.61	0.01			33.50	0.18			42.37	0.00

The table shows the mean values of the TPR and FPR measures. The results of the cross-validation and testing processes are given in two separate rows for each subject and each mental task. The selected CSM and AR orders for each case are also included in the table.

Table 3.
Cross-validation and testing results of the better channel selection method for 5-channel systems.

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Subject	Process	Visualization				Multiplication				Object rotation				Motor imagery			
		dAR†	dTPR†	dFPR†	p-value‡	dAR	dTPR	dFPR	p-value	dAR	dTPR	dFPR	p-value	dAR	dTPR	dFPR	p-value
1	Validation	–8	1.31	0.00	0.2063	7	−5.61	0.00	**0.0004**	5	−2.04	0.00	0.0593	16	−5.11	0.00	**0.0029**
	Testing		0.29	0.00	0.7615		−5.24	0.00	**0.0005**		−1.78	0.00	0.2160		−4.57	0.00	**0.0201**
2	Validation	−2	1.59	0.00	**0.0121**	4	2.40	0.00	0.1009	5	−0.19	0.00	0.8667	−5	4. 82	0.00	**0.0000**
	Testing		1.63	0.00	0.3012		2.88	0.00	0.0654		−0.43	0.00	0.7867		4. 16	0.00	**0.0095**
3	Validation	6	−1.37	0.00	0.3534	9	−4.96	0.00	**0.0005**	6	−3.07	0.00	0.1215	−3	0.91	0.00	0.1889
	Testing		−2.19	0.00	0.0620		−6.10	0.00	**0.0001**		−3.19	0.00	0.1863		1.51	0.00	0.1076
4	Validation	−26	6.36	0.00	**0.0004**	−7	2.43	0.00	0.1970	0	0.67	0.01	0.5523	−2	2.90 –	0.01	0.0878
	Testing		6.41	0.00	**0.0021**		1.98	0.00	**0.0146**		1.83	−0.01	0.0756		2.27 –	0.01	0.0777

† *$dV = V_{\mathrm{MDelete}} - V_{\mathrm{MForm}}$, $V \in \{AR, TPR, FPR\}$.*
‡ *$p < 0.05$ means "there is a significant difference." These cases are shown in bold.*

Table 4.
The difference in performance between MDelete and MForm for the 5-channel systems.

Subject	Mental task	Mental task		
		Multiplication	**Object rotation**	**Motor imagery**
1	Visualization	**0.0146**	0.1759	0.1427
	Multiplication		0.2472	**0.0053**
	Object rotation			**0.0251**
2	Visualization	0.7203	0.1695	**0.0330**
	Multiplication		0.2499	**0.0408**
	Object rotation			0.2949
3	Visualization	0.3236	**0.0049**	**0.0040**
	Multiplication		**0.0034**	**0.0001**
	Object rotation			0.1062
4	Visualization	**0.0000**	**0.0000**	**0.0000**
	Multiplication		**0.0000**	0.8060
	Object rotation			**0.0000**

$p < 0.05$ means "there is a significant difference." These cases are shown in bold.

Table 5.
p*-values calculated using Welch's t-test between the four mental tasks for each subject (5-channel systems).*

TPR values of the two test groups are significantly different. If $p \geq 0.05$, the null hypothesis cannot be rejected at the 5% significance level. This implies that there is no significant difference between the TPR values of the test groups.

The p-value between MDelete and MForm for each mental task of each subject is given in **Tables 4** and **7** under the p-value column. **Table 8** shows the results of the t-test between any 2 of the four mental tasks for each subject in the 7-channel BCIs.

5. Summary and discussion of results

Table 4 shows that the performance of the 5-channel BCI systems obtained using MDelete is close to those obtained using MForm for the majority of the cases. The same is true for the 7-channel systems (**Table 7**). From **Tables 3** and **6**, it is shown that MDelete yields better results in nine out of the 16 cases of the 5-channel BCIs and in seven out of the 16 cases of the 7-channel BCIs.

5.1 System performance of 5-channel BCIs

From **Tables 3** and **5**, we find the following:

1. The FPR values are zero for all 5-channel BCIs of Subjects 1, 2, and 3 during the cross-validation and testing processes, irrespective of the task type. For Subject 4, this is also true for the sentence visualization task-based BCI: the BCI based on the multiplication task has 0.01% FPR for the testing process, the BCI based on the motor imagery task has an FPR of 0.01% for the cross-validation process, and the BCI based on the object rotation task has FPR values of 0.20 and 0.18% for cross-validation and testing, respectively.

Subject	Process	Visualization				Multiplication				Object rotation				Motor imagery			
		CSM	AR	TPR	FPR	CSM	AR	TPR	FPR	CSM	AR	TPR	FPR	CSM	AR	TPR	FPR
1	Validation	**2**	**63**	**63.23**	**0.00**	**2**	**73**	**65.91**	**0.00**	**1**	**64**	**65.45**	**0.00**	1	69	63.35	0.00
	Testing			**63.70**	**0.00**			**64.51**	**0.00**			**66.11**	**0.00**			62.51	0.00
2	Validation	**2**	**62**	**64.59**	**0.00**	**2**	**61**	**63.07**	**0.00**	**2**	**60**	**61.55**	**0.00**	1	64	59.39	0.00
	Testing			**64.77**	**0.00**			**62.73**	**0.00**			**61.97**	**0.00**			60.68	0.00
3	Validation	1	64	63.32	0.00	**2**	**56**	**69.94**	**0.00**	1	65	66.33	0.00	1	65	64.57	0.00
	Testing			64.90	0.00			**70.51**	**0.00**			64.73	0.00			65.32	0.00
4	Validation	**2**	**79**	**61.56**	**0.00**	2	95	51.90	0.00	2	129	27.58	0.01	1	97	49.30	0.00
	Testing			**59.71**	**0.00**			50.21	0.00			27.36	0.01			50.00	0.00

The table shows the mean values of the TPR and FPR measures. The results of the cross-validation and testing processes are given in two separate rows for each subject and each mental task. The selected CSM and AR orders for each case are also included in the table.

Table 6.
Cross-validation and testing results of the better channel selection method for 7-channel systems.

Subject	Process	Visualization				Multiplication				Object rotation				Motor imagery			
		dAR†	dTPR†	dFPR†	p-value‡	dAR	dTPR	dFPR	p-value	dAR	dTPR	dFPR	p-value	dAR	dTPR	dFPR	p-value
1	Validation	**2**	−1.77	0.00	0.1354	7	−6.70	0.00	**0.0017**	3	0.58	0.00	0.5591	1	1.71	0.00	0.3435
	Testing		−2.56	0.00	**0.0084**		−5.12	0.00	**0.0047**		0.80	0.00	0.5357		2.36	0.00	0.1876
2	Validation	**2**	−1.58	0.00	0.0954	4	−2.25	0.00	0.1739	6	−0.70	0.00	0.6486	4	1.25	0.00	0.4317
	Testing		−2.24	0.00	0.0960		−0.44	0.00	0.7226		−2.48	0.00	0.2445		2.58	0.00	**0.0045**
3	Validation	−**2**	1.00	0.00	0.4971	6	−4.86	0.00	**0.0007**	4	0.73	0.00	0.7233	4	−0.06	0.00	0.9542
	Testing		2.22	0.00	**0.0455**		−5.42	0.00	**0.0009**		0.91	0.00	0.6633		1.52	0.00	0.1110
4	Validation	−**3**	−1.59	0.00	0.2486	−5	1.62	0.00	0.1907	−3	4.26	0.01	**0.0173**	5	0.00	0.00	1.0000
	Testing		−0.37	0.00	0.7741		2.26	0.01	**0.0037**		4.02	0.00	**0.0012**		0.54	0.00	0.7501

†*$dV = V_{\text{MDelete}} - V_{\text{MForm}}$, $V \in \{AR, TPR, FPR\}$.*
‡*$p < 0.05$ means "there is a significant difference." These cases are shown in bold.*

Table 7.
The difference in performance between MDelete and MForm for the 7-channel systems.

Subject	Mental task	Mental task		
		Multiplication	**Object rotation**	**Motor imagery**
1	Visualization	0.4889	0.0519	0.3890
	Multiplication		0.2553	0.2243
	Object rotation			**0.0405**
2	Visualization	0.0809	0.1582	**0.0035**
	Multiplication		0.6683	**0.0328**
	Object rotation			0.4601
3	Visualization	**0.0007**	0.9199	0.6681
	Multiplication		0.0135	0.0013
	Object rotation			0.7321
4	Visualization	**0.0001**	**0.0000**	**0.0002**
	Multiplication		**0.0000**	0.8619
	Object rotation			**0.0000**

$p < 0.05$ *means "there is a significant difference." These cases are shown in bold.*

Table 8.
p-*values calculated using Welch's t-test between the four mental tasks for each subject (7-channel systems).*

2. Among all 5-channel BCIs, the highest performance (TPR = 63.72%) is reached by the multiplication task of Subject 3. The object rotation task-based BCI of Subject 4 has the lowest performance with TPR and FPR values of 33.50 and 0.18%, respectively.

3. For Subject 1: multiplication is the best in performance (TPR = 61.24%) although it is not significantly different from object rotation. Motor imagery is the poorest in performance (TPR = 55.30%) although it is not significantly different from sentence visualization.

4. For Subject 2: sentence visualization, multiplication, and object rotation have statistically similar performance with TPRs in the range of 56.00–58.56%. Motor imagery has the poorest performance (TPR = 54.38%) although it is not significantly different from object rotation.

5. For Subject 3: multiplication and sentence visualization have similar and the highest performance (TPRs = 63.72 and 62.68%). Object rotation and motor imagery have similar and the lowest performance (TPRs = 55.37 and 58.51%).

6. For Subject 4: sentence visualization has the best performance (TPR = 53.89%), and object rotation has the poorest performance (TPR = 33.50% and FPR = 0.18%).

5.2 System performance of 7-channel BCIs

From **Tables 6** and **8**, the following are found:

1. The FPR values reach zero for 15 out of the 16 cases. That is for all cases except for the object rotation task of Subject 4, which has 0.01% FPR for each of the cross-validation and testing processes.

2. The results as to which BCIs yield the best and worst performance are exactly as those in the 5-channel systems. Among all the 7-channel BCIs, the best performance with a TPR of 70.51% is reached by the BCI based on the multiplication task of Subject 3 (which is better than the TPR = 63.72% of the corresponding 5-channel BCI). The object rotation task-based BCI of Subject 4 has the worst performance with TPR and FPR values of 27.36% and 0.01%, respectively (which is also better than the FPR = 0.18% of the corresponding 5-channel BCI).

3. For Subject 1: motor imagery is significantly different from object rotation. All other cases are statistically similar to each other. The TPR varies in the range 62.51–66.11% for different mental tasks.

4. For Subject 2: sentence visualization, multiplication, and object rotation have statistically similar performance with TPRs in the range of 61.97–64.77%. Motor imagery has the least performance (TPR = 60.68%) although it is not significantly different from that of object rotation.

5. For Subject 3: multiplication has the highest performance (TPR = 70.51%). Sentence visualization, object rotation, and motor imagery have similar performance with TPRs in the range of 64.73–65.32%.

6. For Subject 4: sentence visualization has the best performance (TPR = 59.71%), and object rotation has the poorest performance (TPR = 27.36% and FPR = 0.01%).

5.3 Discussion of results

Comparing **Tables 3** and **6**, it can be noticed that increasing the number of channels from five to seven enhances the performance of every BCI by an increase of 5.38% in TPR on average (see **Table 9**). Therefore, there is a trade-off between using fewer channels and having better system performance. The choice should be made depending on the applications, the situations in which the BCI system is used, and the computational power available.

In terms of the AR model orders, the 5-channel BCIs need higher orders than the 7-channel BCIs. According to **Table 9**, the overall mean of the AR model order is 98 and 73 for the 5-channel and 7-channel BCI systems, respectively.

Studies [105–109] have also used high AR model orders in their analyses. The AR model order depends on the sampling frequency [106]. Since our sampling frequency is 500 Hz (which is high), then the AR order can also be high. In other words, if the AR order belonging to the sampling frequency 100 Hz is 25, then the AR order belonging to sampling frequency 500 Hz is 125. This is because:

1. The AR order is the number of previous samples of the signal that represents the current sample of the signal. Please refer to Eq. (1) in Appendix A.

2. An AR order = 25 at freq = 100 Hz means that we need the last 0.25 s of the signal to represent the current sample. For freq = 500 Hz, we will need the last 0.25 s of the signal, and thus the AR order would be $0.25 \times 500 = 125$.

	5-channel design			7-channel design			29-channel design†		
	AR	**TPR**	**FPR**	**AR**	**TPR**	**FPR**	**AR**	**TPR**	**FPR**
Average over tasks									
Subject 1	92*	58.51	0.00	67*	64.21	0.00	24	68.54	0.00
Subject 2	89*	56.72	0.00	62*	62.54	0.00	19*	70.38	0.00
Subject 3	87	60.07	0.00	63*	66.37	0.00	20*	70.80	0.00
Subject 4	125	43.09	0.05	100	46.82	0.00	29	59.31	0.00
Average over subjects									
Visualization	90	58.23	0.00	67	63.27	0.00	21*	68.95	0.00
Multiplication	100*	56.38	0.00	71*	61.99	0.00	24	67.38	0.00
Object rotation	101	51.15	0.05	80*	55.04	0.00	24*	65.71	0.00
Motor imagery	102*	52.64	0.00	74*	59.63	0.00	23*	67.00	0.00
Total average	98*	54.60	0.01	73*	59.98	0.00	23	67.26	0.00

†*Results of study [110].*
**The value is rounded to the nearest integer.*

Table 9.
Average performance of the BCI systems.

From **Table 9**, it can be easily recognized that the system performance depends on the subject and the mental task. Among all subjects, Subject 3 has the BCIs with the highest average performance with average TPRs of 60.07 and 66.37% for the 5-channel and 7-channel systems, respectively. Subject 4 has the least average performance with an average TPR of 43.09% for the 5-channel systems and 46.82% for the 7-channel systems.

Among the mental tasks, sentence visualization and multiplication are the best tasks overall. Object rotation and motor imagery yield the least performance on average.

Table 9 also shows the average performance of the 29-channel systems over the subjects and mental tasks for comparison purposes [110]. It can be seen that by decreasing the number of EEG channels from 29 to 7 and 5, the system performance degrades by a decrease of 7.28 and 12.66%, respectively, in TPR on average. This degradation in the system performance is the trade-off one has to make to have a simpler system that can be easily set up and requires less computational power.

6. Conclusion

This study shows that it is feasible to design self-paced mental task-based BCIs with a zero false activation rate using very few (i.e., five or seven) EEG channels. The system performance was evaluated on a dataset we collected from four subjects. Although the evaluation was carried off-line, the methodology can be used in real-time self-paced systems after slight modifications. This is because the feature extraction and the classification processes are not computationally demanding, and there is no need for the timing information of the EEG signals after training the classifier with the training data.

The best performance of the BCI systems described above has zero FPRs and sufficiently high TPRs (i.e., 53.89–63.72% for the 5-channel systems and 59.71–70.51% for the 7-channel systems). Hence, in terms of the system performance, they are acceptable for use in real-life applications. As reported in the study [110], the best performance of the BCI systems with 29 channels has zero FPRs and 65.06–72.65% TPRs.

The frequency domain analysis of the recorded EEG signals is left for future work. By finding the frequency bands with the high amounts of information, we may be able to decrease the sampling frequency from its current value of 500 Hz.

In this study, the EEG trials are divided into 1-s segments for classification, and the BCI system gives an output every 0.2 s. Finding the optimum values for the segment length and the system output rate is the other directions for future work. The use of these values might result in a more accurate system.

Running online experiments is the most important step that needs to be taken in the future in order to evaluate the performance of our BCI system in real time.

A. Autoregressive modeling

The autoregressive (AR) model of the signal $s[t]$ is defined as

$$s[t] = \sum_{j=1}^{F} b_j s[t-j] + n[t] \tag{1}$$

where F is the order of the model, b_j is the jth coefficient, and $n[t]$ is the noise (or error) signal. The noise signal is assumed to be a random process with a zero mean and a finite variance.

In this study, the AR model is estimated using the Burg algorithm [111] which is a popular and widely used algorithm in the field.

There are some methods based on the reflection coefficient [112], the final prediction error criterion [113], the autoregressive transfer function criterion [113], and the Akaike information criterion [113] to find the order of the AR model; however, none of them are efficient in BCI applications [100]. In our previous study [100], it is suggested that instead of using the existing methods, it is better to select the model order by cross-validation based on the system performance. The same approach is taken in this study.

B. Quadratic discriminant analysis

Quadratic discriminant analysis (QDA) [114] is the quadratic version of linear discriminant analysis (LDA). Like LDA, normal distributions are assumed for the classes. The only difference between QDA and LDA relates to the covariance matrices of the classes. In QDA, unlike LDA, the covariance matrices of the classes are not assumed to be the same. Therefore, QDA is more general than LDA.

Suppose we have k-dimensional vectors of x to be classified into one of the M classes with the normal distributions

$$\Omega_m \sim N_k(\mu_m, \Sigma_m) \tag{2}$$

where $m \in \{1, 2, \ldots, M\}$, μ_m is the k-dimensional mean vector and Σ_m is the $k \times k$ covariance matrix of Class Ω_m.

The probability density function of Class Ω_m can be expressed as

$$f_{m,X}(x) = \frac{1}{(2\pi)^{k/2}|\Sigma_m|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu_m)^T\Sigma_m^{-1}(x-\mu_m)\right) \tag{3}$$

Based on the Bayes discriminant rule, the input vector x is classified into Class Ω_i if

$$C_i\pi_i f_{i,X}(x) = \max_j \left(C_j\pi_j f_{j,X}(x)\right), j \in \{1, 2, \ldots, M\} \tag{4}$$

where π_i is the *a priori* probability of Class Ω_i and C_i is the total cost of misclassifying a member of Class Ω_i to the other classes. Note that

$$\sum_{j=1}^{M} \pi_j = 1. \tag{5}$$

The decision rule can be simplified as follows if only two classes exist:

$$x \in \begin{cases} \Omega_1 : C_1\pi_1 f_{1,X}(x) \geq C_2\pi_2 f_{2,X}(x) \\ \Omega_2 : C_1\pi_1 f_{1,X}(x) < C_2\pi_2 f_{2,X}(x) \end{cases} \tag{6}$$

This is equivalent to

$$x \in \begin{cases} \Omega_1 : \ln f_{1,X}(x) - \ln f_{2,X}(x) \geq \ln\left(\frac{\pi_2}{\pi_1}.\frac{C_2}{C_1}\right) \\ \Omega_2 : \ln f_{1,X}(x) - \ln f_{2,X}(x) < \ln\left(\frac{\pi_2}{\pi_1}.\frac{C_2}{C_1}\right) \end{cases} \tag{7}$$

Using (3) in (7), the discriminant rule becomes

$$x \in \begin{cases} \Omega_1 : F_{qd}(x) \geq 0 \\ \Omega_2 : F_{qd}(x) < 0 \end{cases} \tag{8}$$

where the discriminant function, $F_{qd}(x)$, is defined as

$$\begin{aligned} F_{qd}(x) = &-\frac{1}{2}x^T\left(\Sigma_1^{-1} - \Sigma_2^{-1}\right)x + \left(\mu_1^T\Sigma_1^{-1} - \mu_2^T\Sigma_2^{-1}\right)x \\ &-\frac{1}{2}\ln\left(\frac{|\Sigma_1|}{|\Sigma_2|}\right) - \frac{1}{2}\left(\mu_1^T\Sigma_1^{-1}\mu_1 - \mu_2^T\Sigma_2^{-1}\mu_2\right) \\ &-\ln\left(\frac{\pi_2}{\pi_1}.\frac{C_2}{C_1}\right) \end{aligned} \tag{9}$$

The mean vectors (i.e., μ_1 and μ_2) and the covariance matrices (i.e., Σ_1 and Σ_2) are estimated from the data samples. In this study, the same value for the *a priori* probabilities π_1 and π_2 and the same value for the cost parameters C_1 and C_2 are assumed.

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Chapter 5

Neural Signaling and Communication

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Abstract

To understand the complex nature of the human brain, network science approaches have played an important role. Neural signaling and communication form the basis for studying the dynamics of brain activity and functions. The neuroscientific community is interested in the network architecture of the human brain its simulation and for prediction of emergent network states. In this chapter we focus on how neurosignaling and communication is playing its part in medical psychology, furthermore, we have also reviewed how the interaction of network topology and dynamic models of a brain network.

Keywords: cognitive science, brain imaging, neural networks, network topology

1. Introduction

Network science makes advances for modeling and analyzing the variations in communications. Network science has proved useful for functional brain connectivity assumptions and predicting incipient network states. Research in neural network science or neural information processing has been proven fruitful in the past, providing useful methods both for practical problems in computer science and computational models in neuroscience [1, 2].

The human brain shows a discrete spatiotemporal organization that aids brain function and can be imitated via local brain simulation [3]. Such disturbances to local cortical dynamics are globally merged by discrete neural systems [4, 5]. Brain function depends upon complicated active interactions between distinct brain regions that define neural systems. This system-level architecture and dynamics can be discovered across different scales, from microscopic groups of cells to macroscopically defined brain areas [6–9]. Late neuroimaging works have been subservient in mapping the structural and functional architectures of the human brain at the macro scale [10, 11].

Recent developments in the field of cognitive neuroscience require computational and theoretical apprehension of neural information processing models which accomplish standards and constraints from cognitive psychology, neuroscience, and computational efficiency [12, 13]. Nowadays, mapping structural connections and recording temporal dependencies among local time series have become feasible, yet signal transferring across the network in flexible and adaptive computational manner remains unidentifiable.

1.1 Psychiatric disorders and network science

Psychiatric disorders have conflicts related to progression arbitrated by the brain. Developing sign recommends that precise biomarkers might use from integrating information about several brain realms and their connections with one another for psychiatric disorders, instead of seeing local disturbances in brain structure and function [14]. Current progress in the discipline of applied mathematics mostly and network science explicitly offer a language to captivate the complication of cooperating brain sections, and the use of this language for essential inquiries in neuroscience forms an incipient field of network neuroscience. This chapter provides an outline for the application and usefulness of network neuroscience in psychiatry and how network science may cooperate with it.

Most approaches are generally used for animal or human models reckoning however the approach is invasive. The term invasive is specified in this framework as a process that needs a carving in the skin or insert of an apparatus in the body [15].

2. Use of scientific and clinical tools to reconcile unhinge brain activity

Non-invasive brain stimulation such as transcranial magnetic stimulation and invasive brain stimulation such as profound brain stimulation is employed for scientific and clinical tools to unhinge brain activity. Incomparable conditions in which procedures classically kept for experiments on animals, for instance, invasive electrophysiology, can be morally employed in humans. For instance, throughout convinced sorts, I human brain surgery, clinical decisions are controlled by invasive electrophysiological measurements (e.g., ECoG). Along with their medical employment, these recordings also provide expressive information for scientific studies.

Equally, human neuroscience application tools and modeling in animal neurology has aided to expose a fundamental mechanism of these systematic ways. A major illustration is the research separating, cause of practical MRI (fMRI) signal by joining invasive electrophysiological measurement with fMRI in animal experiments.

3. Psychiatry experiments on living being

Naturally, experimenting on animal use invasive electrophysiology, in which electrodes are entrenched straight in the brain for recording action potency and local field potential (LFP and EEG). Furthermore, recording neuronal action by ocular means, calcium and voltage imaging mostly, have become a coercive observational strategy that embellishes electrophysiology in animals although it is well invasive [15]. Optogenetic manipulations (optical measurements and perturbations) can use light to unhinge neuronal activity.

In humans, MRI (magnetic resonance imaging) empowers detailed, non-invasive visualization of brain anatomy. Measurement in blood oxygenation variation as a substitution for neuronal activity can also employ corresponding expertise. On the other hand, electroencephalograph can noninvasively measure electric fields generated by the neuronal activity. Magnetoencephalography and electrocorticography (ECoG) are two less commonly used but significant methods that measure brain signaling. Electric and magnetic fields stimulations record from the brain along with modulating neuronal activity.

Moreover, classifying deliberated systematic ways as whichever noninvasive or invasive will concentrate on the *spatial or temporal resolution* these systematic ways provide.

3.1 Temporal resolution

Temporal resolution discusses how much time does a measurement requires to be completed, and hence states the quickest fluctuations in the signal of attention that can be seized exactly [16]. The sampling rate defines the temporal resolution. The frequency of measurement is referred to by the sampling rate. For example, only a second is required to obtain a single image of human fMRI activity scan (sample rate is 1 Hz i.e., 1/s). Thus, signals that expressively fluctuate in a given sub-second time scale (i.e., any given 1 s interval) are not captured properly. This contrasts noticeably to the typical sampling rate of an EEG device (1000 Hz and greater). A millisecond timescale of action potential fire is the fastest temporal scale [17].

3.2 Spatial resolution

Spatial resolution refers to the specified measuring strategy that can be taken for least events in space. As an illustration, the brain activity of a cubic millimeter resolution is commonly measured using an fMRI. Indifference, the EEG tested natural signals show deprived spatial resolution as they initiate from indefinite square centimeters of brain tissue [18, 19]. Now centering our attention to the spatial scales reaching out of the full brain to distinct neurons [18]. Since there are in cursive methods present for spatial and temporal resolution improvement. For instance, the spatial resolution for electrophysiological brain activities can be as slight as a 100 mm for transcription; electrodes are surgically implanted into the brain. The invasive transcriptions cater to perfect temporal and spatial resolution along with high temporal resolution of electrophysiological measurements. It is prominent that along with some omissions noninvasive approaches accompanying high temporal resolution (e.g., EEG) are subjected to poor spatial resolution and contrariwise (e.g., fMRI). Consequently, merging appropriate approaches has persisted as one of the utmost prevailing and electrifying procedural approaches in network neuroscience [19].

4. Network neuroscience framework

Network neuroscience conceives brain functions as egress from the collective action of various system elements and their common interconnections as shown in **Figure 1**.

Figure 1.
Basic steps of neuroscience framework.

Currently, large-scale efforts to record neuronal connectivity in various species, including the nematode worm, fruit fly, mouse, macaque, and human, have led to a burst of data developed using a diverse array of measurement methods, and at scales fluctuating from a level of single cells to large brain areas. In similar, quick developments in physics of multifaceted network have directed to a new thoughtful of the association and dynamics of systems of interacting elements, with nervous systems being but one example. The confluence of these approaches lies at the core of network neuroscience, which is linked with understanding how nervous systems function as combined systems [20]. Network neuroscience offers one of the rarely incorporated frameworks for revealing different kinds of brain imaging data, needed in different specifies at various scales and have various measurements methods, by demonstrating all nervous systems in their most intellectual form: as assemblies of nodes connected by edges.

Network neuroscience technique has before now produced many novel visions into brain organization, for example, that nervous systems across scales and species illustrate a hierarchical, segmental and minor-world organization, that they contain decidedly connected hubs, they are economically reinforced. As the field develops, tools and methods settled in other areas of network science are being progressively polished and modified to the neuroscience context [9, 20].

The interpretation of how brain egress from a large number of communicated patterns of neuronal elements stands as one of the most abiding challenges of modern neuroscience. The complex systems draw close to understanding the brain is similar to other disciplines that intermix concepts from network science, the study of social networks through statistical physics and dynamical systems, the propagation of epidemics, rumors or computer viruses, the effects of disturbances or assault on electrical grids or the World Wide Web, or the performance of gene regulatory or metabolic networks [21].

5. Brain network topology and communication

Brain network has a topology with prominent attributes that describe the system as a whole: heterogeneous level and strength dispersions, high clumping and short path lengths, a multi-scale modular organization and an obtusely connected core of high-degree nodes are some of the network characteristics which are shared across species and scales.

Similar to any new field, the best ways for manufacturing and analyzing brain networks are still undergoing development. Amid late evolutions is the understanding that brain networks are essentially multi-scale entities.

The term "scale" can have varying meanings depending upon the context; at present we concentrate on three possible definitions related to the study of brain networks. Foremost, a network's spatial scale refers to the coarseness at which the nodes and edges are defined and can vary from that individual cell and synapses [18]. Secondly, networks can be qualified over temporal scales with accuracy varying from sub-millisecond to that of the entire lifespan, to developing changes across various species. Lastly, networks can be examined on divergent topological scales varying from individual nodes to the network as a whole [17, 21]. Conjointly, these scales specify the axes of a 3D space in which any synthesis of brain network data lives. Major brain network analysis subsists as points in the space—i.e., they concentrate on networks specified singularly at one temporal, spatial, and topological scale. We contend that, when studies have proven enlightening, in order to better understanding the brain's actual multi-modal, multi-scale nature, it is important for our network analysis that we begin analysis to form bridges which join different scale to each other [1, 21].

5.1 Routing communication

Routing communication covers the control of paths that data can take over a network. Specified that physical networks have predetermined limits on links, and memory, the main work of routing is to assign paths so that one or extra communication goals are retrieved (e.g., cost, fidelity, fault-tolerance, speed, etc.). Routing is of strongly important for brain's communication via network: inferring sensory data, access of memory, decision making, and several further essential brain functions require that communications can be flexibly directed and acknowledged by several nodes at broadly parted positions on the network, in reply to fluctuating demands [19].

Though, for the reason that of new scientific growths, nowadays the brain is more dynamic than we supposed. The human brain continuously creates new neurons and makes neural pathways during our whole life cycle. Therefore, neurons are dynamic cells that are regularly familiarized to fluctuating situations. If some activity damages an individual's brain (such as an injury or stroke), the neurons have the potential to create a new communication route/path around the injured area. This capability is known as *neuronal plasticity*.

In communication networks, the abbreviated path between two nodes has a special role: the extent of the abbreviated path is taken to the topological distance amid nodes. Hence, the abbreviated path extent is referred to as the indicator of comfort with which signals can be transmitted amid nodes [19, 20].

5.2 Information routing and functional integration

Any solo cognitive function may contain numerous dedicated areas whose association is facilitated by the functional integration between them. Such integration is facilitated by information exchange between brain areas by the means routes that can change with highest timescales at which the structure is fixed, by providing changeable actual connectivity in spite of the inflexibility of the infrastructure on high timescales [9, 11]. The dynamic nature of the information routing and flexible effective connectivity is worth of the multistability of the cooperative dynamics of the brain networks. In addition, single structural connectivity can support numerous degenerate dynamical states, each of which information transfer by use of special pattern can be seen in **Figure 2**.

The modeling of spatiotemporal dynamics underlying integration and segregation can reveal casual mechanics insights into neuropsychiatric disorders. For being influenced by the full potential of whole-brain computational modeling, it is a requirement to capture temporal evolution of brain's functional network organization along with time-averaged representations of FC (which are strongly inhibited by the SC) *in silico* neural dynamics (a neuromorphic analog chip is presented that is capable of implementing massively parallel neural computations while retaining the programmability of digital systems).

Neuronal collective oscillations are assumed to offer such a basis for the dynamic's communication among brain regions. Numerous lines of experimental evidence and theoretical influences specify that the stage relations amongst the oscillations of various brain regions can modify effective connectivity by modulating the result of mutual influence between them.

A more existent account of the consolidative capacity of neuronal systems needs a significant differentiation between the concepts of "communication efficiency" and the usually employed graph theoretic measure called "global efficiency." The mean of the reversed abbreviated length between all pairs of nodes is referred to as the global efficiency, hence captivating the global capacity of the network to transfer information in a collateral fashion [1, 9, 11, 19, 20].

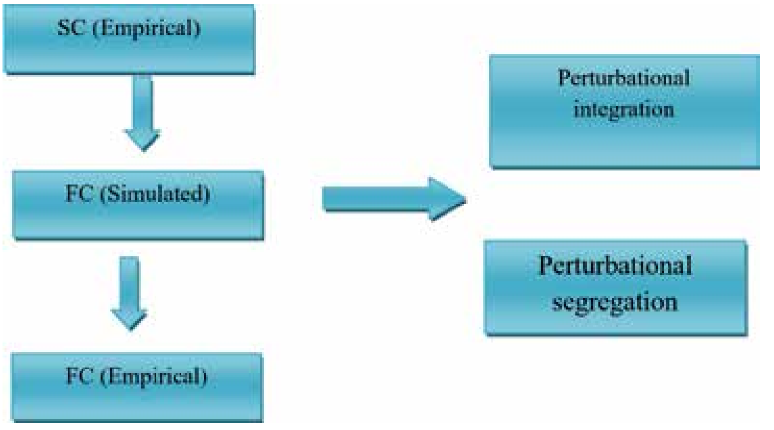

Figure 2.
Information routing and functional integration.

5.3 Network dynamics and communication

Synchronized complete brain neural dynamics are important for appropriate control of functionality in different brain systems, effectual integration of composite and multimodal information, and even adaption to transient regular circumstances. Specified such roles of macroscopic, brain dynamics in our mental and neural information processing, it is sensible to assume that the irrationality of large-scale neural dynamics is a main biological mechanism fundamental autism spectrum disorder (ASD), which is described as the weakening of global information processing.

Structural topology is constricting signal extension is a very important dynamical point of view the communication process. One of the eminent differentiations between dynamical and topological analyses of brain communication is the quantity of information (in the statistical sense) which is required for the extension of the communication process.

5.4 Network computation and communication

The crucial role of communication dynamics in neural computation attracts a great amount of curiosity. Some important and distinct features of brain network communication that enlightens mechanisms by which the brain network carries out computation are as follows:

1. Communication dynamics are effective connectivity.

2. Computation by networks.

6. Multi-scale community structure

The attributes of local and global networks are unambiguous to calculate as the unit analysis of individual nodes and the entire network are closely manifest and no extra search is required. Multi-scale structure, though are not always apparent. The occurrence or nonappearance of multi-scale structures is contingent upon the formation of edges between the nodes of a network known as network topology. Real-life networks consist of numerous nodes and edges organized in complicated outlines which can be ambiguous structural symmetries. Because of such complication, if anyone wants to see a mesoscale structured network, he will have a necessity to algorithmically quest for it. In community structure circumstances, there is no lack of algorithms to do so. They depend on how they describe communities along with computational complexity. The range of the method is observed as a deficiency or a benefit, the originality in community detection and repeatedly increasing subfields of network analysis are desirably settled. Although respectively community detection methods suggest its own possessive exceptional perception on how we can classify communities in networks, the technique that is furthermost extensively employed and debatably the often useful is modularity expansion. Modularity expansion divides a network's nodes into communities so as to make the most of a verifiable function acknowledged as modularity (or just "Q"). The comparison of the practical pattern of connections in a network contrary to the perceptual structure that would be likely below a stated null model of network connectivity is performed by the modularity function. The weight of a respective existent edge is compared directly to the weight of the similar edge if, connections were to be shaped under the null model. Nearly, the ascertained connections will be improbable to subsist under the null model or might it be worthier in comparison to the null model expectations.

The efforts to locate several conceivable robust than predictable connections inside communities is done in the maximization of modularity. Much clearly, if the weight of the ascertained and anticipated connections between the nodes i and j are specified as A_{ij} and P_{ij}, separately, and $\sigma_i \in [1, \ldots, K]$ shows the communities of K in which i can be allotted, then modularity can be calculated as:

$$Q = \sum_{ij} [A_{ij} - P_{ij}]\delta(\sigma_i \sigma_j). \tag{1}$$

Where Kronecker delta function is denoted by δ and is equal to 1 only if arguments are not 0 and are the same. Various methods used in fact to maximize Q, however in conclusion the entire outcome in the estimation of community network structure, a separation into communities. Unfortunately, in the partition, the number and size with the biggest Q represent communities not always demonstrated in the network. Other alike quality functions and modularity show a "resolution limit" which bounds detectable communities' size. Smaller size communities are rather undetectable. In one way to determine all size communities, modularity prolonged in current years to comprise ɣ, a resolution parameter, which can be used for exposing different sized communities. Augmented modularity equation then shows like this:

$$Q(\gamma) = \sum_{ij} [A_{ij} - \gamma P_{ij}]\delta(\sigma_i \sigma_j). \tag{2}$$

Primarily familiarized method for avoiding resolution limit is known as the resolution parameter. Accidentally, it has imparted the flexibility of modularity measure. The resolution parameter acts as a turning protuberance, making attaining of estimated small communities probable when it is at one situation and bigger communities while it is an alternative situation: while ɣ is big or small maximizing modularity will give parallel minor or major communities. With a smooth tune, from one extreme, the resolution parameter can efficiently find evaluations to the other extreme of a network's community structure, from the finest scale from where network nodes form singleton communities to the unrefined scale where all nodes fall in the same communities. Multi-scale community detection can be recognized as the changing resolution parameter for notifying the communities about various sizes. It must be renowned that there subsist possible descriptions of modularity functions which do not endure from resolution limits in the initial place.

7. Conclusion

In the recent past, the network cognitive science has revealed that how the network topology and dynamics outline the flow of neural signal under the brain function to great extent but still there are many gaps remain in our understanding due to data limits and of recording tools. For example, the limited availability of observational tools limits empirical access to communication dynamics. Now a day, it has become possible to map structural connection and recording temporal dependencies among local time series, but the possible mechanism involved in signal transfer across the network in a various manner that allows flexible and adaptive computation remain elusive. In spite of limitations, there is a wide range of opportunities to learn how the brain network functions. The nature of communication may vary, for example, dynamic network model is kind of theoretical framework that is helpful in an understanding of our knowledge of behavior and cognitive science, it also includes the pattern of change with aging and development. Furthermore, it can become an important tool for predicting the effects and outcomes of perturbations, including lesions and focal stimulation. Building on topology and dynamics, the confluence of empirical and theoretical studies are poised to add significant new insights into the network basis of brain function.

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Chapter 6

Integration of Spiking Neural Networks for Understanding Interval Timing

Nicholas A. Lusk

Abstract

The ability to perceive the passage of time in the seconds-to-minutes range is a vital and ubiquitous characteristic of life. This ability allows organisms to make behavioral changes based on the temporal contingencies between stimuli and the potential rewards they predict. While the psychophysical manifestations of time perception have been well-characterized, many aspects of its underlying biology are still poorly understood. A major contributor to this is limitations of current *in vivo* techniques that do not allow for proper assessment of the di signaling over micro-, meso- and macroscopic spatial scales. Alternatively, the integration of biologically inspired artificial neural networks (ANNs) based on the dynamics and cyto-architecture of brain regions associated with time perception can help mitigate these limitations and, in conjunction, provide a powerful tool for progressing research in the field. To this end, this chapter aims to: (1) provide insight into the biological complexity of interval timing, (2) outline limitations in our ability to accurately assess these neural mechanisms *in vivo,* and (3) demonstrate potential application of ANNs for better understanding the biological underpinnings of temporal processing.

Keywords: interval timing, time perception, neural oscillators, dopamine, basal ganglia, artificial neural networks, spiking neural networks

Highlights

- Examine neural signatures, circuitry dynamics, and neuromodulator pathways related to interval timing behavior
- Address limitations in current *in vivo* techniques in studying timing
- Discuss the use of artificial neural networks for understanding neural dynamics and timing
- Identify properties of thalamocortical dynamics that may be integral to time perception

1. Introduction

When it comes to understanding the neural underpinnings of time perception, the devil is in the details. As all events inevitably unfold in time, there is no shortage of potential "timing" signals. However, behavioral tasks often possess inherent relationship between time, spatial location, and external signals making it difficult to isolate activity dedicated to timing per se. As a result, timing correlates have been observed across nearly all regions of the cortex [1–4] as well as sub-cortical areas and the cerebellum [5, 6]. Reflecting this anatomical diversity, the number of theoretical models dedicated to timing is also vast, and utilize a diverse range of firing dynamics such as oscillatory [7] ramping [8] or synfire chains [9]. Yet, which of these various timing motifs and to what degree they contribute to a unified perception of time remains unclear [10].

A contributing factor to the multitude of timing theories are the limitations of current *in vivo* techniques, which can be spatially restrictive, produce ambiguous information, and contain representation biases. Though remarkable strides have been made in expanding the scope of techniques used to record, image and modulate neural activity, the capacity to selectively manipulate and/or effectively observe the propagation of activity from a large population of neurons within a particular brain region or across multiple regions, is limited. With theories of temporal processing spanning the microscopic level of intrinsic cellular [11, 12] and network dynamics [13–15] to the macroscopic interplay between multiple brain regions [16], understanding how animals track the passage of time has been an arduous task through reliance on *in vivo* techniques alone.

A promising avenue to help circumvent the aforementioned limitations is the integration of biologically inspired ANNs. While neural networks have been around for over half a century [17], recent years have seen a resurgent interest in their development and application within neuroscience. Spurred by substantial advancements in computational power, the ability for labs to integrate complex, biologically constrained neural networks is more viable than ever before. As the integration and development of biologically inspired ANNs into neuroscience has been steadily growing for many decades, adoption into the field of time and time perception has been comparatively slow.

Though examples do exist, current efforts have remained limited [18–20]. Moreover, these networks often lack characteristics considered vital for biologically realism such as bidirectional activation propagation or Hebbian-based learning [21] - characteristics that see widespread use in other fields. Many of these models utilize rate-based units, applying 'activation functions' and highly simplified network motifs, limiting the temporal dynamics of the network. While these simplified

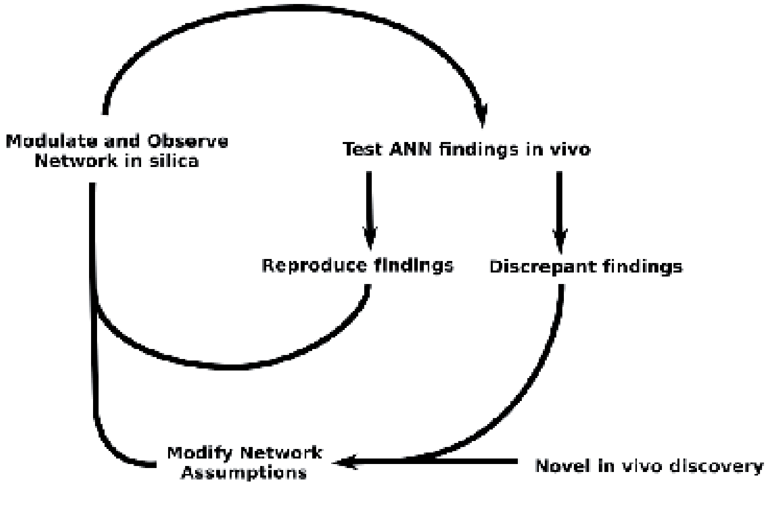

Figure 1.
Proposed cycle for integration of SNNs. Schematic visualization of integrating SNNs into empirical process.

networks provide valuable theoretical insight, the incorporation of spiking neural networks (SNNs) with biologically inspired 'spiking' units and network architectures, allows SNNs to capture neural dynamics more analogous to the biological systems which they are based and a more critical assessment of timing theories. The integration of SNNs can allow researchers to visualize the propagation of temporal information as well as finer control over neuromodulatory systems not possible in other models.

The aim of this chapter is to demonstrate how the field of timing and time perception can benefit from the implementation of biologically constrained SNNs. In so doing, limitations of current *in* vivo recording and imaging techniques will be addressed along with examples of how SNNs can be used to circumvent such constraints and facilitate hypothesis driven research (**Figure 1**). Lastly, specific outstanding questions in the field of interval timing that could most benefit from integration of SNN models will be identified.

2. Interval timing networks and dynamics

Neural correlates of time perception have been observed across nearly the entire cortical mantel. In theory, any pattern that remains consistent for a given duration yet varies across durations is capable of acting as a biological timer. As these requirements are not particularly stringent, electrophysiological recordings have uncovered many candidate patterns. The prefrontal cortex (PFC) alone contains ramping, peaking, and oscillatory activity meeting such criterion [22–26]. In addition to spiking activity, EEG and MEG recordings in humans [27–29] demonstrate a robust relationship between mesoscopic oscillations and timing behavior.

2.1 Cortical spiking and mesoscopic oscillations

Electrophysiological studies in rodent and non-human primates have shown robust correlations between cortical activity and timing behavior across multiple brain regions. Yet, how dynamics within and across cortical regions contribute to these behaviors are still unclear. Though ever expanding, limitations in our current knowledge on how information propagates across interconnected brain regions has made drawing causative relationships between timing behavior and specific neural signals difficult.

One of the most studied neural correlates of timing is 'ramping activity' (**Figure 2A**). These monotonic increases or decreases in firing rate have been observed within the prefrontal [25, 26] primary motor [30] and posterior parietal cortex [31, 32] during various timing tasks. Along with its seemingly ubiquitous presence within the cortex, key observations further indicate ramping as a viable timing mechanism: (i) ramping activity has been demonstrated to occur across multiple timescales from hundreds of milliseconds to multiple seconds (ii) the rate of change can be adjusted through learning different durations (iii) the rate of change during a reproduction task is dependent on the presented duration. Specifically, neuronal activity in the lateral inferior parietal cortex (LIP), recorded in macaques trained on a temporal reproduction task, found changes in firing rate were inversely proportional to the duration being produced. That is, shorter durations had steeper ramping activity therefore reaching threshold sooner [31].

However, pharmacological inactivation of ramping activity within these same regions of the cortex, namely the posterior parietal cortex (PPC), during evidence accumulation tasks has negligible effects on stimulus categorization [33]. Conversely, decreasing prefrontal cholinergic concentrations reduced temporal

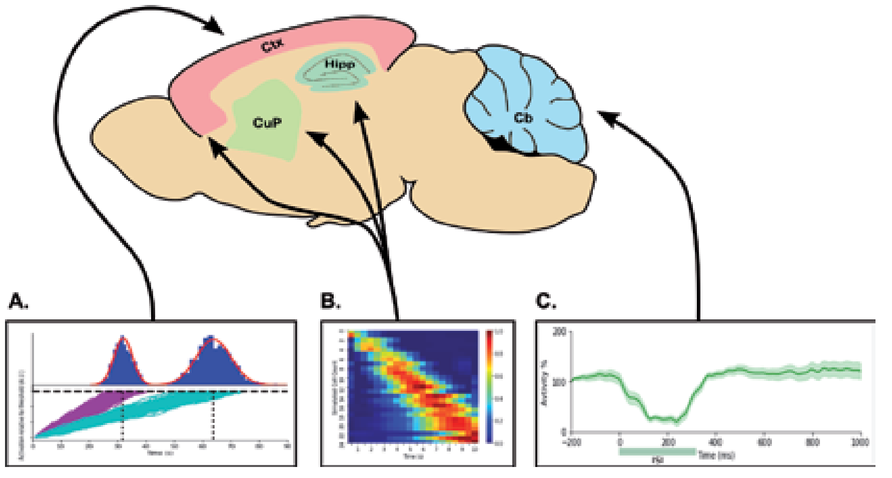

Figure 2.
Distribution of timing correlates and associated activity patterns. (A) Simulation of ramping activity as observed in cortical networks during timing tasks. Parameterized using values from model of neural integration (Simon et al. 2011). Theoretical accumulation of activity (bottom) and distribution of time to threshold (top) (B) Heatmap of simulated activity normalized by max firing rate depicting trajectory dynamics found in the cortex, hippocampus, and striatum. (C) Depiction of pauses in Purkinje cell activity within the cerebellum during 300 millisecond delay (ISI) Pavlovian eye-lid conditioning.

precision without disrupting ramping activity demonstrating a potential dissociation between ramping and timing behavior [34]. Other regions have demonstrated a more causal relationship, namely, ramping in the frontal orienting field (FOF) was found to be necessary for proper performance possibly implicate ramping activity as a general computational motif within cortical circuits of which timing is localized to a particular cortical region.

Recent evidence suggests that neuronal ramping may not, in fact, be ramping at all, but an artifact of bi-stable neuron activity averaged over multiple trials. Analysis of spiking activity within the LIP during individual trials of a motion discrimination task showed 31 of 40 neurons exhibited 'stepping' behavior [35] as opposed to the deterministic gradual increase expected of a truly ramping dynamic (c.f. [36, 37]). These findings parallel human studies which have cast doubt on the role of the contingent negative variance (CNV) – an EEG correlate of ramping activity – in temporal processing due to the poor predictive ability of the CNV and the high temporal accuracy demonstrated even after the resolution of the signal [38]. How ramping activity develops also remains unclear [39, 40].

Larger scale recordings, containing 55–120 simultaneously recorded neurons, have painted a relatively different picture of spiking activity within the cortex during timing. Bakhurin and colleagues [22] found putative projection neurons contained activity patterns in which individual neurons in the orbital frontal cortex (OFC) displayed sequential activity that tiled a 1.5 s delay period following an olfactory cue. This type of firing is reminiscent of "time cell" activity recorded in other brain regions such as the striatum [6, 41] and hippocampus [42, 43] providing a parsimonious representation of timing signals across distinct brain regions (**Figure 2B**).

At the mesoscopic level, oscillatory activity within cortical regions has also been theorized as an underlying mechanism for time perception. As with spiking correlates of timing, neural oscillations are pervasive throughout the brain and implicated in a multitude of cognitive processes such as attention, memory, movement preparation and even consciousness [44]. Yet, their computational role in these processes is generally unresolved [45]. Nevertheless, researchers have long recognized the potential of rhythmically repeating oscillators to track the passage of time from hundreds of milliseconds to tens of minutes [46, 47].

Increases of delta range (~4 Hz) oscillations in the medial prefrontal cortex (mPFC) were shown to negatively impact the temporal precision of rats performing a 12 s fixed-interval task. Pharmacological attenuation of these increases in delta through blockage of D1 dopamine receptor (D1DR) signaling mitigated the associated deficits in timing [2]. Interestingly, D1DR+ neurons in the prefrontal cortex have strong delta frequency coherence with a subset of neurons exhibiting ramping activity implicating a direct link between microscopic spiking and mesoscopic oscillations during timing [48]. Additional evidence supports the existence of spike phase relationships with the mPFC particularly within the theta frequency (5–10 Hz) [23, 49, 50]. However, Benchenane et al. [23] demonstrated that spike-phase entrainment to theta in the mPFC only occurs during times of high coherence between mPFC and hippocampal (HIPP) theta and is most prominent at times requiring encoding or retrieval of spatial memory. This property likely makes it too transient to track time over multiple seconds. Increases in cortical theta have also been associated with interval timing tasks where sustained increases in cortical theta power occur during the encoding of the standard duration in a temporal comparison task [51, 52], though whether coherence between HIPP and mPFC remains high across this entire duration has not been tested.

As with ramping activates relation to timing behavior, the coupling of spikes to oscillations appears to be region specific. Though oscillatory activity has been observed within the cortex across multiple frequency bands, there is limited support for individual neurons firing-rates to entrain to these rhythms. For example, though timing behavior correlates with cortical beta (~15–30 Hz) activity within the dorso- and ventro-lateral prefrontal cortex, premotor cortex, and posterior parietal cortex [28], recent work suggests that spiking activity demonstrates minimal coupling to beta rhythms [53].

2.2 Neuromodulators and time perception

Timing behavior has been shown to be highly susceptible to manipulations of neuromodulators such as dopamine (DA: [54–58]) serotonin (5-HT: [59–61]) and acetylcholine (Ach: [34, 62, 63]). Additionally, patients suffering from disorders involving these pathways [64–66] demonstrate systematic changes in their timing ability.

Dopamine has been the most widely studied neuromodulator in the field of interval timing. Despite this depth of research, many questions still remain as research has produced seemingly paradoxical effects. Early psychopharmacological studies demonstrated bidirectional shifts in timing accuracy (i.e. over- or underestimations of a target duration) after administration of DA agonists and antagonists, respectively [55–57, 67]. This work suggested that DA changes the speed of a subjects internal timing mechanism (i.e. "clock speed" effect). This could manifest itself as changes in the slope of ramping neurons or oscillator frequency. However, other research suggested that administration of dopaminergic drugs such as the selective D_2 and D_3 agonist Quinpirole disrupts timing precision rather than accuracy through modifying attentional processes [58, 68]. While later work using a variation of the peak interval procedure supported the changes in accuracy, the directionality of the peak shifts did not align with the original "clock speed" hypothesis [69]. Subsequent experiments further demonstrated these effects to be sensitive to non-temporal aspects of the task similar to the "attentional modulation" hypothesis.

The wide repertoire of timing behaviors related to DA modulation may be a product of its diffuse circuitry [70, 71]. Alternatively, the complexity may result from interactions with other neuromodulatory pathways. Electrophysiological evidence suggests DA neurons elicit tonic excitatory control over 5-HT neurons within the raphe nucleus [72]. In fact, a mouse model of Parkinson's disease using 6-OHDA lesions lead to increases in spontaneous firing as well as maximum firing rate of 5-HT neurons in the dorsal raphe nucleus [73].

Administration of 5-HT_{1A} receptor agonist 8-OH-DPAT modulated timing precision on retrospective timing tasks, while immediate timing tasks saw changes in accuracy [74]. However, the contribution of 5-HTergic pathways to timing behavior remains precarious as many of these studies were unable to dissociate changes in interval timing from intertemporal choice [60]. In fact, more recent work indicates 5-HT to be more strongly associated with intertemporal choice [75] along with additional factors such as reward rate and temporal uncertainty [76]. This relationship appears to be bidirectional as 5-HT projections from the dorsal raphe nucleus can modulate DA release directly through excitatory synapses onto VTA dopamine neurons [77]. A selective 5-HT_{2c} ligand shown to increase vigor and persistence in goal-directed behavior also leads to increased tonic DA levels in the dorsal medial striatum [78]. The aforementioned interaction within the DMS is likely driven by excitation of striatal cholinergic interneurons which can drive action potentials independent of DA release [79, 80]; thus, linking cholinergic pathways to an already complex system.

Despite considerable work on the role of neuromodulators in timing behavior, dissociating the mechanisms responsible for these effects is yet to be fully understood. These systems contain multiple origins with diffuse and overlapping targets. Moreover, direct as well as indirect connections between these pathways makes it difficult to confidently assign credit to a single pathway and behavioral changes are often dependent on the parameterization of the particular study. As a result, it is likely that non-traditional methods allowing for more systematic modulation of the respective pathways is necessary to fully disentangle their individual roles in timing behavior.

3. Limitations of current *in vivo* techniques

Substantial advancements of *in vivo* techniques are now allowing for exceptional insight into neuronal dynamics. The number of simultaneously recorded single neurons has seen a near doubling every 7 years [81]. Coupled with growth of open-source hardware systems, access to these powerful technologies is becoming more feasible and cost effective [82]. However, these techniques are still limited in the amount of information they are able to reliably produce in relation to the dynamic properties of the brain. This has led to debate into the sufficiency of correlations between firing activity and behavioral output. Additionally, many of the current methods used for manipulating endogenous activity suffer from a lack of specificity. The aforementioned diffuseness of the interval timing network coupled with sensitivity to neuromodulation limit the insight from *in vivo* techniques alone.

3.1 Recording and imaging

Extracellular *in vivo* recordings have long been the technique of choice for linking neural activity to ongoing behavior through monitoring action potentials (APs) along with more mesoscopic neural activity in the form of local field potentials (LFP). Though Advancements in recording techniques has been able to mitigate some of the uncertainty in isolating an individual cell's activity, a sizeable degree of error still exists. Though quantification of this error, referred to as the 'spike sorting problem', is difficult due to the lack of 'ground truth' data, estimates suggest semi-automatic clustering error with tetrodes to be on the order of 5–10%, and substantially higher (upwards of 30%) for manual cluster cutting, a process still popular in many labs [83]. Furthermore, the uncertain origin of signals such as gamma range oscillations makes interpretations speculative [84].

A second class of errors that can lead produce specious conclusions is 'selection bias'. Combined intra- and extracellular recordings within CA1 of the hippocampus demonstrated that despite an estimated 140 neurons within the recording distance of a single tetrode, rarely are more than a dozen signals ever detected [85]. While innocuous contributions such as acute edema and glial encapsulation can lead to significant decreases in signal strength and subsequent cell counts [86], other causes such as under classification of cells with low firing rates can skew researcher's interpretation of genuine network dynamics. Furthermore, differential firing rates between regions, such as higher firing rates in deep-layers of the cortex in comparison to pyramidal cells of the superficial-layer [87, 88], may bias researchers toward studying areas with high spiking and subsequently overestimating a regions role in the overarching circuit. Recent attempts at addressing and quantifying the quality of *in vivo* recordings is a step toward lessening the effect of electrical artifacts [89, 90], though further work in this direction is still needed.

In addition to classic recording techniques, calcium imaging has become a popular tool for visualizing activity. Imaging permits precise spatial mapping of activity [91, 92] and mitigates many of the limitations in recording such as the "spike sorting problem" and "cell selection bias'" [93]. Further improvements in fluorescent indicators [94, 95] and scanning techniques [96] have been able to overcome past limitations in sampling rate allowing for detection of somatic calcium transients evoked during action potentials.

However, in non-laminar low cell density brain regions the number of cells that can be simultaneously observed is highly restricted. Sub-cortical areas such as the striatum can be limited to less than 40 cells [97] and require significant damage to regions dorsal to those being imaged. Paired with the inability to sufficiently account for dynamic interactions within a single brain region imaging technique are even more limited when attempting to study interactions across multiple regions. In all, while *in vivo* techniques are one of the most valuable tools for understanding the relationship between neural signals and behavior, alternative methods in conjunction can provide richer insight into not only regional dynamics, but also interregional interactions.

3.2 Pharmacological, chemogenetic, and optical manipulations

While electrophysiological recording and imaging provide insight into endogenous activity, much of our knowledge into how the brain senses the passage of time has arisen from the manipulation of timing networks. Yet, there are often deviations between a researcher's intent and the actual alterations within the brain. The main contributors are lack of specificity or incomplete knowledge of the technique being used.

While the foundation of many theories in time perception, pharmacological manipulations are the most susceptible to confounding interactions. Even drugs touted as selective can display affinity for non-target receptors. Concretely, the commonly used D1-antagonist SCH-23390 also demonstrates high affinity for serotonin receptor subtypes 5-HT_2 and 5-HT_{1C} [98]. While its affinity for D1 receptors is much higher than that of 5-HT, the expression of both receptor types within this region could explain why timing behavior following local infusions of SCH-23390 into the DMS has been difficult to interpret [99]. As $5\text{-}HT_2$ activation within the striatum has been shown to indirectly reduce striatal MSN activity [100]. Conversely, timing effects attributed to serotonin could be mediated through or in conjunction with indirect increases in DA, which has been demonstrated in $5\text{-}HT_2$ agonists such as Psilocybin [101].

In an effort to minimize off-target effects there has been a renaissance in the development of chemogenetic and optogenetic techniques. Vaunted for their ability to mitigate the confounds of pharmacological methods, a growing literature is revealing these approaches come with their own set of drawbacks. While chemogenetic approaches such as DREADDs (Designer Receptors Exclusively Activated by Designer Drugs) has helped alleviate some of the uncertainty from pharmacological manipulations, recent work shows that CNO (clozapine N-oxide), the most commonly used agonist in DREADDs, can back metabolize into clozapine and has the potential to accumulate in amounts capable of activating endogenous receptors [102]. Importantly, clozapine has been demonstrated to affect temporal accuracy as well as the flexible use of timing mechanisms [103, 104]. While this limitation can be addressed through the use of proper CNO controls in addition to transitioning to low-dose clozapine, these steps constrain DREADDs extended duration of action, likely its greatest advantages over optical techniques.

As with chemogenetic approaches, optogenetic methods have not been immune from technical setbacks, even after widespread implementation. Despite over a decade of use in neuroscience, new caveats in the effectiveness of microbial opsins are still being discovered. pH-dependent calcium influxes from sustained activation of inhibitory proton pump opsins such as eArch3.0 can increase spontaneous neurotransmitter release during terminal stimulation [105]. Inhibitory Cl- channels (i.e. eNpHR3.0 & GtACR1), on the other hand, can drive axonal spiking through positively shifted chloride reversal potentials leading to unintended spiking at the onset as well as offset of stimulation [105, 106].

4. Artificial neural network in timing (ANNs)

Despite being inspired largely by neuroscience, ANNs were initially touted for their powerful computational versatility rather than reliable models of neural or cognitive phenomena. Since their conception, the emergence of conductance-based units, biologically inspired architectures and learning rules has made them an invaluable tool for elucidating how the brain works.

4.1 Importance of spiking neural networks (SNNs)

The 'neuronal' unit embodies the fundamental computational element of an ANN and plays a vital role in the overall capacity of the network. As such, computational neuroscientists have dedicated substantial work transforming early 'neuronal' units, based on the binary threshold unit (i.e. McCulloch-Pitts neurons) into conductance-based 'spiking' models [107–111] that include both detailed biophysical models and simple phenomenological models. Implementation of SNNs allows for rate and temporal dynamics nearly equivalent to those found in biological systems [112].

However, with the increased biological complexity comes an increase in computational cost (i.e. number of floating-point operations per 1-ms of simulation). This has led many to opt for computationally simpler units with continuous 'activation-functions' rather than spiking dynamics. While these 'rate-based' networks have proven successful in revealing network architectures conducive to timing [113] as well as how shifts in excitability drive timing activity [114], they remove temporal components of neural signaling related to that limit their explanatory power. Electrophysiological evidence from neural recordings within the superior temporal sulcus (STS: [115]) and motor cortex (M1: [116]) indicates the brain relies heavily on temporal coding (i.e. coherent inputs). Importantly, increases in coincident spiking correspond with temporally relevant timepoints independent of changes in firing rate [117].

SNNs thalamocortical [118] and corticostriatal [119] networks, both implicated in proper timing behavior, found sharp transitions in spiking activity are important for normal functioning within the network. This speaks to the diversity of spiking patterns present in the brain that can be captured by spiking units [120], yet absent in rate-based networks. The strongest advocates for SNNs question whether any evidence exists for rate-coding with in the brain [121]. Thus, placing the onus on those who utilize rate-based networks for not choosing SNNs.

Additionally, SNNs allow for implementation of both Hebbian and error-based learning rules. This is of note as the network learning rule can have dramatic effects on the connectivity and dictate whether it develops a feedforward topology scarce in both closed and unique loops or strong reciprocal connectivity motifs like those found in the neocortex [122, 123]. Implementation of these spiking neuron models can lead to dramatic improvements in network performance [124]. The effects of neuromodulators on plasticity also contain tight temporal windows (0.3–2 s) between glutamate release and the presence of DA [125, 126], which is difficult to properly model in rate-based models.

4.2 Current use of SNNs in timing research

Generally absent from earlier ANNs, implicit and/or explicit representations of time within neural network models have been relativity recent [127]. Despite this late adoption, there has been a recent surge in research devoted to elucidating the neural substrates of temporal processing, with a myriad of distinct network motifs being proposed [128]. These models vary in biological realism as it pertains to unit dynamics, network structure, and learning capabilities (**Table 1**), influencing not only the dynamical repertoire of the network, but also the ability to extrapolate findings into the biological systems they are looking to study. That being said, even in their most simplistic form, with little adherence to known biology, network models can provide theoretical insight [132], but these models are highly limited.

Adherence to the underlying neurobiology, allows network models to provide deeper understanding into neural substrates of temporal processing. As interpreting *in vivo* pharmacological manipulations must be done with caution, with many drugs acting on multiple neuromodulatory systems, the ability to isolate these neuromodulatory systems in SNNs allows for uniquely systematic approach. Specifically, a cortico-striatal network model allowed researchers to isolate the effects of changing DA concentrations, free of potential 5-HT confounds, and replicating DA's effect on 'clock speed' [130]. In this same model, modulation of Ach produced the accuracy changes found from systemic injections of drugs acting on the cholinergic pathway [67]. Interestingly, Ach modulation in a hippocampal network produced variations in task precision [134] rather than accuracy. Taken together, these networks may provide evidence indicating dissociated networks for these effects. More recent work has also helped elucidate the potential topographical mapping of duration length across the dorsal-ventral axis of the hippocampus [129, 135].

Study unit	**Unit type**	**Network properties**			**Learning rule**		**Findings**
		Lateral inhibition	**Recursive**	**Modulators**	**Hebbian**	**Error driven**	
Oprisan et al. [129]	Spiking* (ML)	No	No	N/A	No	No	Hipp. Topology; K*
Oprisan and Buhusi [130]	Spiking* (ML)	No	No	Ach, DA	No	No	Modulator in SBF framework
Reutimann et al. [131]	Spiking (LIF)	No	No	N/A	Yes (rate)	No	FR adaptation accounts for 'ramping' activity
Hilton and Parter [132]	Spiking (prob. threshold)	No	No	N/A	No	No	Connectivity motifs for efficient timing;
Mikael and Gershman [113]	Gaussian 'state' activity	No	No	DA	No	Yes	Bidirectional DA modulation through RPE framework
Laje and Buonomano [19]	Rate units	Yes	Yes	N/A	No	Yes	Intrinsic timing framework; neural trajectories
Simen et al. (2011)	Rate units	Yes	No	N/A	No	Yes	Temporal integration framework; skewness
Perez and Merchant [133]	Spiking (LIF)	Yes	Yes	N/A	Yes	No	Bias property; scalar property

**While a spiking model, membrane potential not spikes where used as unit output.*

Table 1.
Recent publications of ANN models in the study of interval-timing.

At the synaptic level, computational work using leaky-integrate and fire neurons demonstrated hallmarks of temporal processing such as the 'bias property' and 'scalar property' are strongly influenced by GABAb receptor dynamics [133]. While outside the field of interval timing, work looking at the relationship of pre-post spike pairings to spike-time dependent plasticity (STDP) has shown LTP/LTD dynamics are better explained by 'nearest-neighbor' inputs rather than an 'all-to-all' motif [136]. Together, these finding place limits on theories utilizing temporal integration as a potential mechanism for tracking the passage of time, such as those relying on ramping dynamics. Additional theories relating synaptic plasticity to motor-timing, a sub-field of interval timing, are grounded heavily in computational work due to the difficulty of assessing these ideas *in vivo* [137].

These results align with animal work demonstrating how important biophysical features of neuron signaling such as receptor kinetics directly influence the timing of durations up to 100 s of milliseconds [12]. Therefore, researchers must be vigilant in selecting the appropriate level of biological complexity for the question they are looking to address. In this way that time perception may be more sensitive than other senses such as vision, where retention of the biological computations can often be sufficient for producing similarities between representations in higher order processing regions [138].

While the above examples have focused on the ability of SSNs to provide support for particular theories, these models have proven to be equally useful in excluding alternative theories as well. For example, ramping activity in the cortex, a potential neural manifestation of timing, can arise from various network architectures. Two such networks employ either recurrent synaptic facilitation or firing-rate adaptation. Yet, additional firing properties seen during delay response tasks, namely equivalent responding to matching and non-matching stimuli is only evident in networks based on firing-rate adaptation [131]. Additionally, it had been postulated that time perception could evolve from sequentially firing populations of neurons [139] and may underlie temporal pattern formation in song birds - a subset of motor timing [140]. However, recent work demonstrated this architecture is incapable of producing fundamental properties of interval timing such as scale invariance [141]. The ability to cast doubt on proposed timing mechanisms is an important quality of computational models. If the technique was flexible enough to validate all theories, it would be of little value.

4.3 Future directions for SNNs in timing research

Integration of SNN models has proven to be an exciting and fruitful avenue for better understanding neural dynamics related to interval-timing. However, there is still ample room for growth. With the implementation of SNNs still in its early stages, the vast majority of these models lack the biological realism necessary to address open questions in the field. Three areas that have either received little attention or would benefit from greater focus are (1) recurrent interactions between timing circuits (2) Neuromodulator effects on timing signals and (3) biologically based model of temporal learning.

As previously mentioned, time perception is supported by an expansive network of brain regions. However, the vast majority of network models aimed at understanding interval timing are at odds with the multi-regional, recurrent nature of the brain. Models of visual processing have shown recursive networks capture multi-regional cortical dynamics absent in strictly feed-forward models [142] as well as behavioral interactions between reaction time and uncertainty [143]. Recurrent connections may also aid in spontaneously developing high degrees of sparseness within a network like that seen in neocortical circuits [144], which allows for larger networks without compromising effectiveness [145]. In addition to being recursive, connection probabilities vary within and between brain regions. Specifically, cortical areas tend to form ‘small world’ motifs, connecting more often with nearby cells [146, 147].

In other branches of neuroscience, SNNs have shown promise is their ability to selectively manipulate interactions between as well as distinct activity within neuromodulatory pathways. One of particular interest to understanding time perception is phasic and tonic DA signaling. These methods of DA release are believed to be differentially regulated [148] as well as serve different behavioral purposes [149], though our knowledge is still limited. A SNN of the basal ganglia aimed at understanding PD pathology demonstrates, through methodical control of either phasic or tonic activity, that each system differentially contributed to Parkinsonian akinesia and tremors [150]. As tonic-phasic interactions have been shown to have paradoxical effects in drug-seeking behavior [151], SNNs may provide invaluable for understanding how individual modulation of these two DA dynamics may contribute the paradoxical effects seen in interval timing studies of DA.

SNNs also offer deeper insight into how different neuromodulatory pathways interact in order to produce learned behaviors. Investigating the computational roles of neuromodulated STDP in the hippocampus, researches demonstrated the importance of DA and Ach interactions on learning during a navigation task [134]. Of particular interest was the ability of Ach to enhance precision in navigation, while DA dominated learning overall. This provides insight into a potential mechanism for increases in temporal precision seen from perinatal choline supplementation [152] and dissociates these from changes in accuracy that can accompany increases in precision when Ach is pharmacologically increased [153]. This result expands upon a growing literature dedicated to better understanding synaptic plasticity through spiking neural models [154–156]. Unfortunately, up until this point SNNs dedicated to time perception that have addressed the role of neuromodulators have done so through implementation of their proposed effects, rather than plasticity directly. Additionally, very few models have used a Hebbian learning rule of any type.

5. Limitations of SNNs

The innate connectivity pattern between neurons plays an important role in shaping the trajectory of neural activity within the brain. To this end, biological models can only be as good as our knowledge of the underlying biology. Within the striatum, slight deviations from the biologically relevant range for recurrent connectivity between MSNs is sufficient to suppress the regular sequential firing patterns of coherent cell assemblies found from *in vivo* recordings [157, 158]. While previous neural network models investigating temporal processing within the cerebellum have benefited from its well-characterized, highly conserved cytoarchitecture [159–161], this is not a luxury afforded to those attempting to construct models of other brain regions such as the striatum. Constituting 1.3% of total brain volume in humans [162] and 4% in rodents [163], the dorsal striatum lacks clear internal divisions making it difficult to model accurately. In response, the past decade has witnessed a prodigious effort in mapping the brain's connectivity.

Benefited by advancements in microscopy and neuroanatomical tracing techniques, recent endeavors have uncovered functional domains within regions of the dorsal striatum based on innervation from cortical afferents [164], which can be a valuable tool for modeling timing networks [165]. Further work at the synaptic level will allow for connectivity parameters within neural network models to be tuned more closely tuned to that seen in the brain. However, as this chapter has demonstrated, it is not only through *in vivo* work that our knowledge of the underlying biology can be expanded. Though confirmation inevitably relies on such techniques, theoretical in addition to computational breakthroughs can be done elsewhere.

Along with biological limitations, implementation of many large-scale models – whether in neuron count or complexity – rely on high-speed supercomputers or computing clusters. In labs where computational modeling is not their primary focus, it is impractical to invest the time or money into such resources and therefore places a ceiling on the size and complexity of their simulations. While cost reductions in hardware dedicated to simulating the highly parallel nature of the brain will inevitably address the largest barrier to widespread use of SNNs, providing intuitive software is vital. Along with closed-source options such as MATLAB's, a fervent movement is currently underway in provide highly versatile packages in Python - an open-source, high-level, dynamic programming language. Simulators such as Nengo [166], NEST [167], and Brian [168] provide varying degrees of control over network properties allowing users to model neurons and circuits at various levels and permitting detailed models on general purpose computing hardware [169].

6. Conclusion

The ubiquity of temporal structure within the brain has made identifying the exact neural processes an arduous task. Single- and multi-unit recordings, along with more recent imaging techniques, have revealed a myriad of neural activity profiles which may underlie temporal processing. Despite technical advancements, the complex interactions between neuromodulators, neuronal activity, and timing behavior has left our current understanding of how the brain tracks durations across multiple seconds decidedly unclear. A promising avenue for overcoming the limitation of current *in vivo* methods is the incorporation of practices form outside the field, such as integration of SNNs. Specifically, through observing how temporal information flows in biologically constrained networks as well as how systematic manipulation of individual neuromodulatory systems changes timing behavior.

Though ANNs are already a staple in other domains of neuroscience, their integration into the field of time and time perception has remained relatively rudimentary with limited attention being paid to biological constraints. It is important to note that the use of these models is not for deciding the exact neural mechanism as that is not possible, but only for providing insight into potentially fruitful options. While ANNs relying heavily on algorithmic abstractions can proliferate theoretical models of timing, a prefect digital recreation of the brain exchanges one black-box for another. In this way the use of SNN for understanding time perception is neither truly top-down not bottom up, but best approximated as 'middle-out'.

We are now at a time where widely available computational resources possess the power necessary for construction of SNNs that retain much of the complexity in biological neural networks. The ability to visualize activity profiles and connectivity patterns across thousands of modeled neurons within and across brain regions provides a level of analysis unavailable through current *in vivo* recording and imaging techniques. Furthermore, simulations of potential avenues for future studies can assess the robustness of competing models in their ability to predict behavioral changes from *in vivo* modulation. Deeper integration of SNNs within the field of timing will provide a powerful resource in both understanding the plausibly neural underpinnings of timing within the brain.

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Chapter 7

Introducing a Novel Approach to Study the Construction and Function of Memory in Human Beings: The Meshk Theory

Mohammad Seyedielmabad

Abstract

This study reviews the crucial role of memory in the human brain. For this purpose, previous investigations and researches about the construction and function of memory were studied. The mechanism of the memory function was reviewed, and crucial drivers for the working of the memory were indicated. Then an applied memory model that could serve as a framework to study the memory function was also introduced. Therefore, the memory unit was introduced as a basic information structure. Also, a structured platform for the memory unit was determined for encoding the information and data in the brain. Then a pattern of information coding was detected. Thus, a basic framework to study the memory function was conceived. The results of this thesis pave the way for the discovery of a basic algorithm to understand the memory function in the human. Also, this study introduces a simple way to overcome Alzheimer disease (AD). This way can be applied to research on the prevention and treatment of this disease.

Keywords: Meshk theory, triple drivers, memory model, memory unit, memory coding strand, music therapy, Alzheimer disease

1. Introduction

Memory is one of the greatest unsolved secrets encountered by human generation. There are a lot of questions about memory. The memory remains a mystery until now. A lot of scientists have studied memory, but there have been no certain results until now. Only recently has it been determined that memory is a faculty of the mind. They have discovered that information is encoded, stored, and retrieved in a region which is called “hippocampus” [8]. Also, they have found that memory is vital to experiences and related to the limbic system of the brain [8]. Models of memory provide abstract representations of how memory is believed to work [3]. There are several models that have been proposed over the years by various psychologists [3]. Controversy is involved as to whether several memory structures exist [3]. For decades, neuroscientists have attempted to unravel how the brain makes memories [22]. Atkinson-Shiffrin and working memory are the different kinds of memory models that have been available in the last decades.

The human brain is estimated to have approximately 86 billion neurons [12], and each neuron has tens of thousands of synapses, leading to over 100 trillion synaptic connections [2]. Concurrence monitoring of 100 trillion synaptic connections is an impossible work. On top of this astronomical complexity, one needs to map each connection or neuron to a given stimulus, yet possible numbers of stimuli that can be used are infinite given the complex, ever-changing nature of the world we live in [27]. This is one of the most difficult issues faced by neuroscientists. As such, the unifying mathematical principle upon which evolution constructs the brain's basic wiring and computational logic represents one of the topmost difficult and unsolved meta-problems in neuroscience [1, 9]. Because of that, it is required to introduce an innovative approach to solve this problem. Recently, Dr. Tsien and his colleagues introduced an approach about memory that is known to "thought experiment." They have done a lot of studies in the last decades about memory. It seems that this approach has an important contribution in the area of neuroscience. One useful concept in pursuing this line of reasoning is cell assembly, a term coined by Hebb [11] to describe the supposed computational building block or computational primitive in the brain. This notion has attracted keen interest, especially with emerging large-scale recording techniques [6, 13, 15, 16, 18, 19, 25]. Hebbian cell assembly was postulated to be comprised of a group of neurons with strong excitatory connections that are formed after learning [13, 26]. Dr. Tsien and his colleagues focus their research on the hippocampus, particularly a region called CA1, which is important to forming memories of events and places in both people and rodents [19, 24]. The hippocampus has four parts including CA1, CA2, CA3, and CA4, and each section can be divided into nine sections. The study results of scientists add to a growing body of work indicating that a linear flow of signals from one neuron to another is not enough to explain how the brain represents perceptions and memories [17]. Rather the coordinated activity of large populations of neurons is needed [19]. Human memory is a great performance organ. Also, the memory function is due to its structure. While the architecture of memory detects, it is possible to distinguish the memory function. This approach can be used to overcome neural diseases especially Alzheimer disease (AD) according to music. Alzheimer disease is a neurodegenerative disorder featuring gradually progressive cognitive and functional deficits as well as behavioral changes [4]. More than 30 million people in the world are suffering of Alzheimer disease (AD(. It is a deadly disease that resulted in about 1.9 million deaths in 2015 and therefore is one of the most costly diseases. The previous investigation showed that music has an effect on treatment of AD. It is necessary to carry out a comprehensive study about music therapy of Alzheimer disease. It is a simple and low-cost way that takes less time for prevention and treatment of AD. Music is known as part of mathematics, and music composers work in the field of mathematic rules. In mathematics, a circle has 360°. So, all mathematical rules are in this field of degrees. Therefore, human memory works at 360° and connects to a complete loop. Barbad is one of the first ancient musicians in Kurdistan. He compiled 360 types of music that were made in 200 AC. Kurdistan is a strategic region that was separated to four parts between Iran, Iraq, Turkey, and Syria after World War 1. Kurd is a term that concerns people in Kurdistan that are related to the ancient Sumerians (10). Kurdistan is a historical place that had governments in the ancient periods. One of them is known as Sassanian. In this period, music was prevalent, and many people worked on mathematics, and so, music was built on the structure and function of the human brain. According to this approach, music shows the inherence of human memory. Hence, music can relieve and improve the nerves and memory. The last studies that have been done by a lot of scientist prove this claim. Some of these investigations led to the wonderful discovery. It is required to carry out a comprehensive study about human memory for introducing a simple and applied way to overcome Alzheimer disease. The objectives of this study respond to the following questions:

What is human memory?
What is the simple structure of memory in the human brain like?
How does human memory work?
More importantly, what is a simple way to overcome Alzheimer disease?

2. Methods

2.1 Triple drivers

In Einstein's special theory of relativity, $E = mc^2$, energy and mass are equivalent and transmutable. It is possible to explain the relativity theory of Einstein for the brain. According to Meshk theory, the memory structure and function of the human brain depend on three main factors (**Figure 1**). The word Meshk is known in the Sumerian and Kurdish languages to the human brain. These drivers provide the inherence of human memory as shown below:

Water equivalence conducted by the water driver $\longrightarrow C^2$
Nunch resonance (NR) provided by the energy driver $\longrightarrow E$
Substance (mass) proportion provided by the mass driver $\longrightarrow M$

The human memory in the function circle is based on three basic drivers including water, energy, and substances. Water is a driver for creation and operation of memory. The quantum brain dynamic (QBD) theory claims that water comprises 70% of the brain and proposes that the electric dipoles of the water molecules constitute a quantum field [34, 35]. Therefore, human memory works in a general circle provided by water called "water equivalence (WE)." While memory neurons are working, WE is an important factor for coding and encoding memory information. The last studies have shown that conscious experience correlates not with the number of neurons firing but with the synchrony of that firing [38]. Ears are likely to be related to this process because the ear is connected to the brain's equilibrium process. For a long time, the oldest part of the brain was thought of as a "control

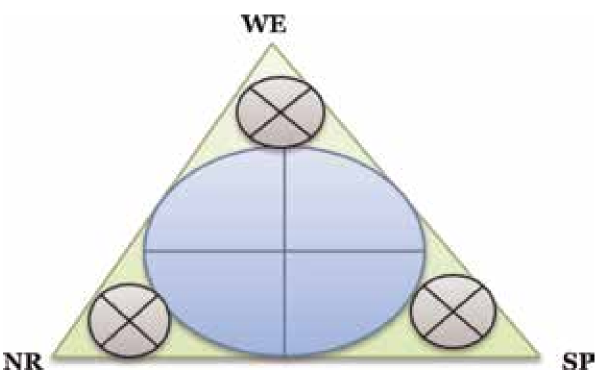

Figure 1.
The triple drivers that provide the inherence of human brain, the gray circles, blue circle, and green triangular indicate the NR, SP, and WE, respectively.

room" for human motions [42]. Now there is evidence that the cerebellum also stores the temporal information about the music we are listening to, and then it recalls this information while reproducing the music [42]. Moreover, an amazing fact is that the cerebellum was discovered to be a center for emotions [42]. Also, the water equivalence of the brain can lead to a powerful electromagnetic (EM) field in the brain. The electromagnetic theories of consciousness propose that consciousness can be understood as an electromagnetic phenomenon [36]. Electromagnetic field theories of consciousness propose that consciousness results when a brain produces an electromagnetic field with specific characteristics [36, 37].

In the conscious electromagnetic information (CEMI) theory, McFadden proposes that the digital information from neurons is integrated to form a conscious electromagnetic information field in the brain [39]. Since the brain is a 300° Kelvin tissue strongly associated with its environment [44], it is possible that the noise and warm environment of the brain cause to transform the water crystals. This transformation, resulting in internal equivalence of the brain, leads to the operation of intrinsic memory. This process can form the basis of memory structure. Dr. Masaru Emoto and colleagues (1996) studied water crystals [31, 32]. They proposed that human consciousness has an effect on the molecular structure of water and therefore emotional energies and vibrations could change the physical structure of water [33]. Brain activities in human infants have shown evidence of existence of the intrinsic memory. The high ability to learn a language in infants is an important evidence that proves this claim. There is a fundamental potential in infants that enables them to advance learning and behaviors. This is a fundamental difference between human beings and others. There is a mechanism in the human brain in which "Nunch resonance (NR)" enables the brain to accelerate and increase reactions to stimuli from the environment. According to **Figure 2**, each nunchaku includes two parts that are linked together by a connection. A part of the nunchaku inputs the force and energy and then transmits it to the other part by a connection. Owing to the resonance in this process, the output force is much more than the input. It is what McFadden termed as "amplifying the microscopic quantum effects." In the CEMI theory, the synchronous firing of neurons is argued to amplify the influence of the brain's electromagnetic field fluctuations to a much greater extent than would be possible with the unsynchronized firing of neurons [39]. Exciting recent research shows that nontrivial quantum effects are present in biological systems and not just in spite of, but sometimes because of, the interaction with the noisy and warm environment [51]. Furthermore, because the brain is a complex nonlinear system with high sensitivity to small fluctuations, it is likely that it can amplify microscopic quantum effects [51]. It is also possible that light photons derived from the eye are related to this process. In general relativity (GR) and the equivalence principle developed by Einstein, it is argued that black holes are regions of space where gravitational attraction is very strong, because even light cannot escape. It is possible that there are spots with a black energy attribute on the front lobe of the human brain. The mineral substances in the function circle of the human brain are provided by a process called "substance or mass proportion (SP)." It is likely that the heart and sense organs are important parts for this process. The concurrence of the triple drivers is required for encoding information in the memory. Triple driver compatibility is required to encoding

Figure 2.
A schematic of the nunchaku function.

information in memory. According to Einstein's special relativity theory, $E = mc^2$, energy and mass are equivalent and transmutable. In this equation, c^2 is the determinative factor, and so it can be concluded that WE is the main driver for recalling information in the brain.

2.2 Memory model

Most of the memory models presented in the past decades have been based on time. The terms of memory, including short-term, long-term, and working memory, are defined by time. In Einstein's special theory of relativity, $E = mc^2$, time and space are not invariable. According to the Meshk theory, space and time are variable and parts of the inherent memory. Therefore, memory in the human brain is indicated in a new model called "Manna model." In this new model, memory is divided into three parts fundamental, central, and peripheral. The base structure of memory in this model is shown in **Figure 3**. Fundamental memory is inherent intelligence. This can be called intrinsic memory and has existed since the advent of mankind. This memory is very cryptic and so unknown so far. The spatial and temporal information are parts of the memory nature. The ability of infants to swim and learn a language is clearly an example that confirms the nature of fundamental memory in human beings. All learning processes in the central memory of human are connected to fundamental memory that is called "recalling of the internal information." The environmental information includes visual, auditory, and sensory data. The eye, ear, and heart are the centers of receiving the visual, auditory, and sensory information from the environment and transmitting them to the brain (**Figure 2**). It is possible that sensitive organs send their signals to the heart and, after coordination, the information is sent from the heart to the brain. The peripheral memory is specialized to receive environmental information from the eye, ear, and heart and transmit them to the central memory. At the start, external information is transferred from the peripheral to the central memory. In the process of being transferred, some of the data is removed, and some remains. By coupling of blocks in the fundamental to the central memory, internal information is retrieved. The "coupling process" is a turning point in reminding of internal information from the fundamental memory. The water equivalence (WE) is an important factor for operating the coupling process. The coupling process can be the starting point for neural momentum in the brain neural circuit. Therefore, in human memory, it is necessary to receive information from the auditory, visual, and sensory systems for making memory coding unit. At the same time, the information in the fundamental and central memory is also binded as binary codes. The coupling process leads to the

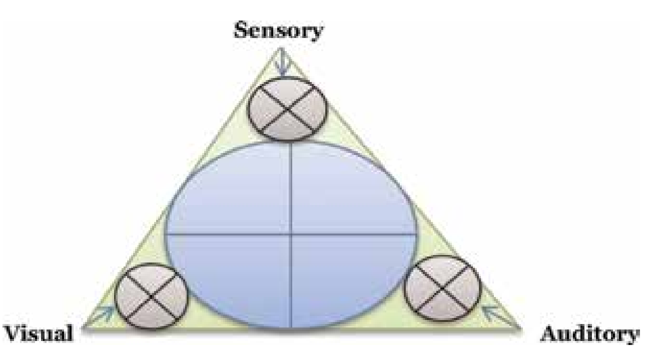

Figure 3.
The Manna model, the gray circles, blue circle, and green triangular indicate the peripheral, central, and the fundamental memories, respectively.

creation of this important structure. This is what Dr. Tsien and colleagues termed as "neural cliques." They discovered that these overall network-level patterns are generated by distinct subsets of neural populations or neural cliques [19].

According to the theory of connectivity by Dr. Tsien, a clique is a group of neurons that respond similarly to a select event and thus operate collectively as a robust coding unit [14, 19–21, 23]. **Table 1** indicates each event as three blocks are active and the others are inactive. The investigators represented clique activity as a string of binary codes that revealed details of the event an animal experienced [19]. In the string fragments shown here, 1 means a particular clique is active, and 0 signifies inactivity [19]. The idea of quantum coherent waves in the neuronal network is derived from Frohlich [35]. He viewed these waves as a means by which order could be maintained in living systems and argued that the neuronal network could support the long-range correlation of dipoles [35]. Repeated stimulation in a continuous and rhythmic way is a critical factor in operating the coupling process. As more and more memory blocks are turned on and active, more processes of recalling the internal information are performed. Therefore, more information and data are extracted from the fundamental memory. In the human brain, there are millions of memory blocks that are not used during the lifetime. Thus, people have entire blocks in fundamental memory but only turn on some of the blocks in their lifetime (**Table 2**). The active blocks make up the central memory in the human brain. The recalling of internal information and data from the fundamental memory is different about people. This process is different from elementary to advanced levels. It is dependent on the quality and the quantity function of coupling process in the memory. In mathematics, the entire angle of a circle is 360 grades (360°). The human brain works in a 360° field and therefore in two mutual directions (**Figure 4**). The Manna alphabet framework is interestingly conformed to the algorithm of the human brain structure (**Table 3**). This alphabet could be the best basic format to receive and transmit data and information by the human. Manna is a term that concerns people to the south of Urmia Lake in Kurdistan [7, 29]. There are a lot of mysteries about the Manna that has not been discovered until now. The

A	**1**	**1**	**0**	**0**	**1**
B	**1**	**1**	**0**	**1**	**0**

Table 1.
The binary codes, (A) earthquake and (B) elevator drop.

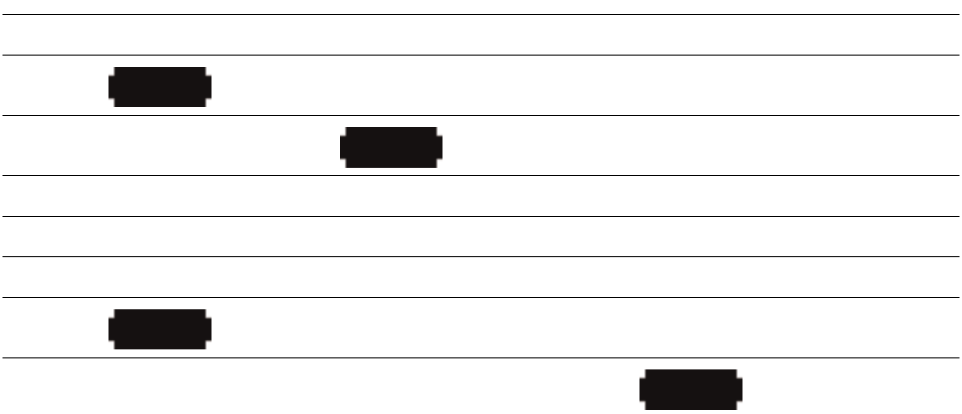

Table 2.
The building blocks of fundamental memory in the human brain. Black blocks are the memory in use, and white blocks are inactive memory.

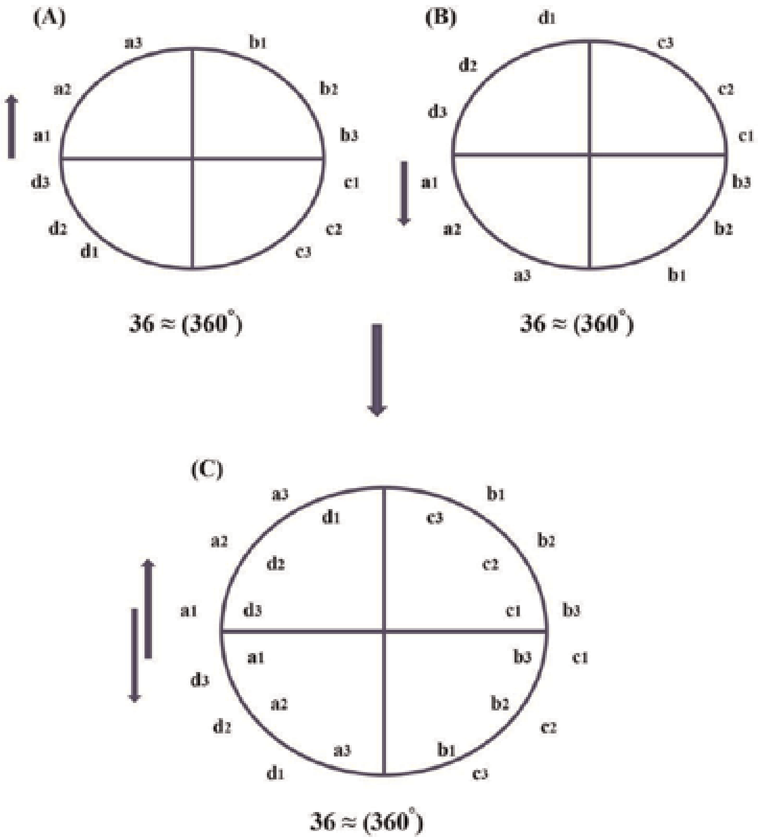

Figure 4.
The circles that indicate the memory coding directions, (A) base direction of the memory coding, (B) complementary direction of the memory coding, and (C) entire directions of the memory coding.

1	2	3	4	5	6	7	8	9	
A	i	U	k^a	k^u	x^a	g^a	g^u	c^a	**A (a1, a2, a3)**
j^a	j^i	d^a	d^i	d^u	t^a	t^u	Θ^a	c^a	**B (b1, b2, b3)**
n^a	n^u	p^a	f^a	b^a	m^a	m^i	m^u	y^a	**C (c1, c2, c3)**
r^a	r^i	i^a	v^a	v^i	s^a	$\dot{S}^a$	z^a	h^a	**D (d1, d2, d3)**

Table 3.
The structure of Manna alphabet between 600 and 800 BC.

only thing that has been distinguished is that the people of that age were blessed with great intelligence. They developed music, agriculture, animal husbandry, industry, medicine, and astronomy. According to ancient literature, Sumerians and Mannea had an advanced alphabet with 37 and 36 letters, respectively [10, 30]. The Mannea were an ancient ethnic group, and a rich trove of literature written by them exists [28, 5]. This literature and books covered various topics including music, agriculture, astronomy, medicine, industry, and more importantly water engineering. The Manna alphabet included four partitions with a specific algorithm, and each part had nine letters. This algorithm made a basic structure for humans to communicate and understand the relation between the people from the ancient period until now. This alphabet can be a suitable pattern for decoding memory architecture in humans.

3. Results

3.1 Memory unit

There is a need for a paradigm shift from behaviorist stimulus-response concepts toward notions of predictive coding in self-organizing recurrent networks with high-dimensional dynamics [45, 47]. Neuronal networks with nonlinear neurons and densely connected feedback loops can generate dynamics that is more complex, variable, and rich than expected [48–50]. Therefore, the two structures of the hippocampus located in the limbic system can operate in reciprocal connection to the coding of the information in the brain. According to the Meshk theory, the information and data received from the environment encode in a structure is called "memory unit." Each memory unit is actually a perception unit in the human brain. It is necessary to operate one or a few perception units to figure out the problems and issues. According to the Manna model features described in the previous sections, each memory unit includes three parts: visual, auditory, and sensory. Therefore, each perception unit makes three functional codes (**Figure 5**). At the same time, the central and fundamental codes are binded together by coupling process to create the binary codes described in the previous section. For an individual event, three sections in the memory unit have to work, and each section has a functional code. It is likely to operate numbers of the memory units for an individual event. This is dependent on the quality and quantity of internal information that might be extracted from the fundamental memory. Locating consciousness in the brain's electromagnetic (EM) field, rather than the neurons, has the advantage of neatly accounting for how information located in millions of neurons scattered through the brain can be unified into a single consciousness. In this way, EM field

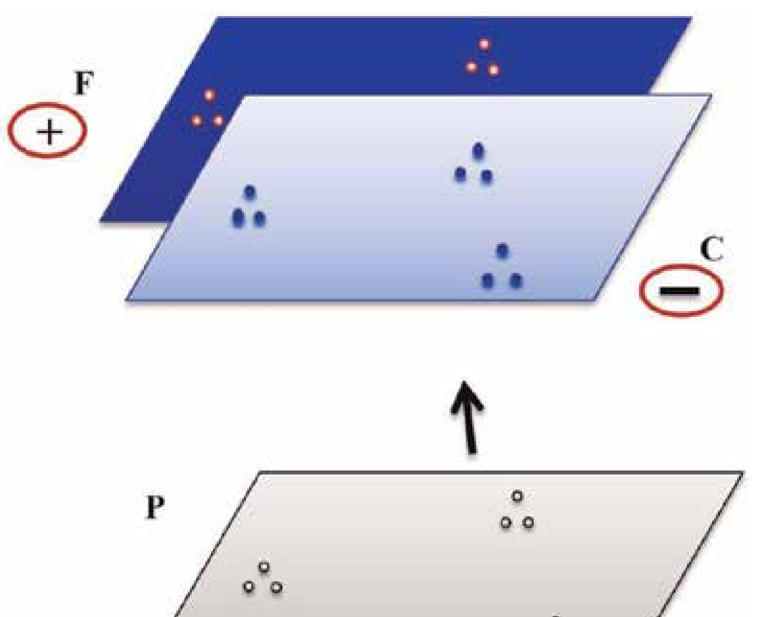

Figure 5.
The coupling of memory blocks in the human brain. Plates F, C, and P show the fundamental, central, and peripheral memories, respectively.

consciousness can be considered to be "joined-up information" [41]. This is an important part of the issue that could help scientist to solve the brain puzzle. When neurons fire together, their EM fields generate stronger EM field disturbances [40]. Therefore, synchronous neuron firing will tend to have a larger impact on the brain's EM field (and thereby consciousness) than the firing of individual neurons [41]. The synchronous neuron firing is like a symphony orchestra or philharmonic orchestra with a lot of musical instruments. The harmony of playing music causes to create of a strong and impressive conclusion. Without each part of the symphony orchestra, the music is imperfect. The generation by synchronous firing is not the only important characteristic of conscious electromagnetic fields as in Pockett's original theory; spatial pattern is the defining feature of a conscious field [36]. In a philharmonic orchestra, there is an accurate spatial and temporal pattern that is well organized. It can lead to creating of a memorable artistic masterpiece. In Meshk's theory, spatial and temporal patterns are part of the intrinsic memory features. The CA1 region of the hippocampus receives inputs from many brain regions and sensory systems, and this feature most likely influences what type of information a given clique encodes [22].

3.2 Memory coding strand

The nervous system can be seen as a nested hierarchy of nonlinear complex networks of molecules, cells, microcircuits, and brain regions [46, 51]. The Manna alphabet has a simple structure for understanding the brain. It is an appropriate programming system for the human brain and could be the first one designed by humans. In this way, the alphabet conforms to the structure of information coding in human memory. Therefore, in the coding process, signals received by the brain from the environment translate into special characters. These characters are arranged based on the external information received from the environment. A recorder strand of information is divided into four parts, and each part includes a memory unit (three memory codes) (**Figure 6**). The two strands of memory, akin to strands of deoxyribonucleic acid (DNA), run in reciprocal connection and are thus parallel. The two strands of memory are coupled together for making a crucial structure. The base strand is made in the fundamental memory, and the couple one is in the central memory. These two strands make memory coding strand that enables the brain to advance learning and behaviors in humans. In this structure, information processing is done in a simple way by the human brain. Therefore, it could possibly be a fast way to distinguish problems and issues. **Figure 7** shows the overall architecture and human memory function in the Manna model. According to this approach, the reminder of the internal information process is carried out in five general stages; A and B have potential levels, and D and E are active levels of

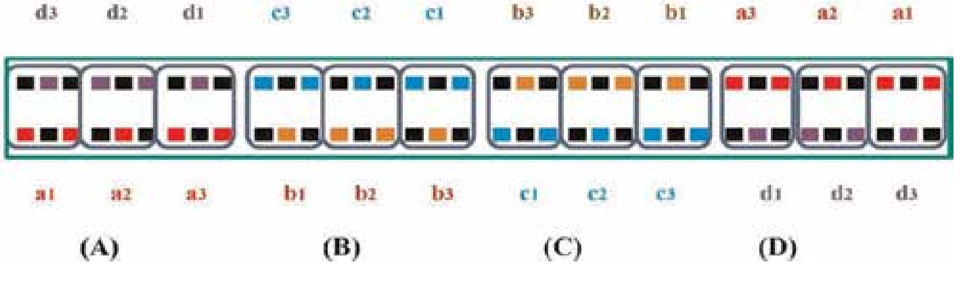

Figure 6.
The pattern of human memory coding. A, B, C, and D are the memory units.

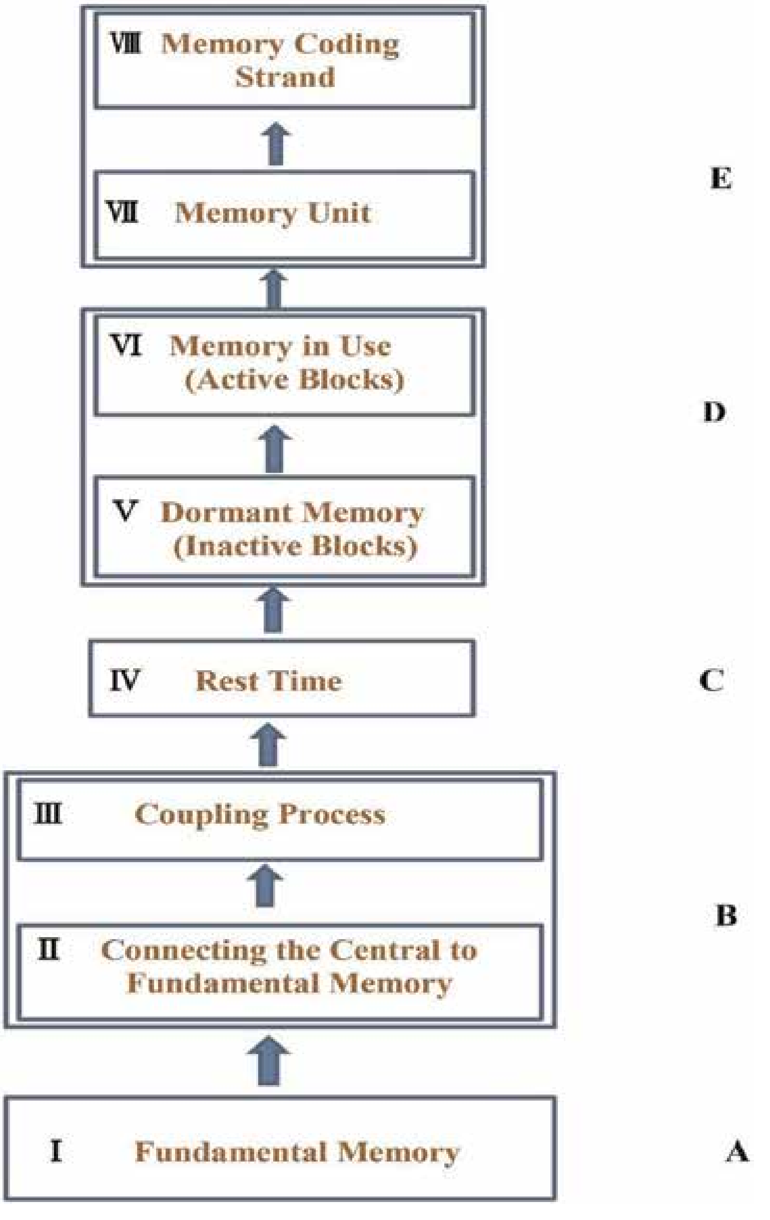

Figure 7.
The functional levels of Manna model.

the memory. In general, in detail of this model, eight levels of human memory function have been deciphered. Also, the basic algorithm for the memory of the human is an exponential function. This function is transcendental and indicates the features of human memory coding. The function is as follows:

$$\mathbf{N = e^{i} - 1} \tag{1}$$

where N is the number of memory units connected in different possible ways; e is the Napier's constant; i is the information they are receiving; and 1 is just part of the math that enables you to account for all possibilities.

4. Conclusion

The fundamental memory in animals is alternatively an ability that is known to instinct. In comparison to the fundamental memory in human, the animal instinct is primitive. It means that animal species have inherent intelligence, but the quality and quantity function of coding the information is different from the human. While the fundamental memory function is known, most problems and ambiguities about memory including short-term, long-term, working memory, and learning process are being answered. For instance, in the Manna model, learning is an activity that is described as a reminder of the internal information from intrinsic memory to central memory. It is said that all of the information and data are in the atmosphere and we have to discover them, but it is likely that internal information is in the fundamental memory. While the learning process is a reminder of information from the fundamental memory, it is required to make a connection between the fundamental and central memory. This connection is made by the coupling process. This process creates memory units and, therefore, leads to the formation of a memory coding strand. Indeed, in the Manna model, the memory unit is a unit of reminder information. In this model, the coupling process is a turning point in the neural circuit and can be the basis of the memory function. Also, like to the structure of Deoxyribonucleic acid (DNA), memory is formed to a spiral train structure. According to general relativity of Einstein, the observed gravitational attraction between masse results from the warping of space and time by those masses. Human memory is made of U shape components that convoluted together. The curvature in the U shape components intensively increases efficiency in the structure and function of memory. The two strands of memory are coupled together for making an applied and unique architecture. In human beings, this architecture is working for advance learning and behaviors. The Manna model is a simple and applied memory model that clearly explains the construction and function of memory. This model provides a functional framework to distinguish the memory function and therefore discover a basic algorithm for memory in the human brain. Consequently, using an applied and simple model, scientists can find a simple solution to overcome the brain and mind disorders, especially for Alzheimer disease (AD).

One of the important solutions to Alzheimer disease is the music therapy that scientists are investigating about. The music utilizes a large variety of basic brain functions; it is closely tied to emotion and seems to be advantageous to survival in line with Darwinian natural selection [43]. It is sometimes claimed that swimming is the best exercise one can do since it requires one to work nearly every group of muscles [43]. The music can be thought of as the brain's analog to swimming [43]. It's a most basic and passive form; it exercises timing functions, matches patterns, and makes predictions [43]. Like swimming as the best exercise to recover and retrieve body muscles, music has the ability to retrieve and remind the brain's internal information. It is necessary to design a technique for music programming in specific time periods. This technique enforces the brain to manage the fundamental memory for the recall of information without using drugs and surgeries. According to the Meshk's theory, a simple technique dubbed as "special music programming" is organized to retrieve memory and mind. This technique is made up of two sections, including harmonic music composes and repetitive courses. Synchronicity of body muscle movement is a basic principle in swimming. Similarly for a particular person, the music harmony and scheduling of repetition time in this technique are key factors that have been ignored in previous research on music therapy of the mind. It is possible to dub these important principles as spatial and temporal equivalence (for a particular person). The repetition of harmonic music in the certain time periods is a turning point in stimulating the mind for recalling information in the Alzheimer disease. This simple technique is divided into 72 sections (36 pairs) each section having special composes and time. Each pair can be performed in a day (morning and one in the evening). Each period is 40 days, because the day after 9 days of the program, there is 1 day to rest the mind. Therefore, there are nine repetition periods in the year. In general, the program includes 324 working days and 36 resting days in the year. This simple technique depends on the architecture and functions of human memory and thus is remarkable to retrieve memory in Alzheimer patients. Also, it is applied to prevent the disease for people in different ages. The Mozart and Beethoven symphonies can be applied in this way, because these symphonies are compatible with the structure and function of human memory. The Kurdish and Iranian traditional music that was named Dastgah, including Mahur, Homayun, Nava, Segah, Cahargah, Rast-Panjgah, and Sur, can be very appealing. According to the Meshk theory, this adaptation is logical and it is not casual. The influence of music and symphonies on the mind has been investigated in the past decades, but is not organized in repeating certain courses (for a special person). That is why previous investigations on the music therapy of the mind have not succeeded and have remained as a cryptic problem up to now. Crucial points of this study can be applied in research about the music therapy of the mind and other investigations.

Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Brain-Computer Interface (BCI) sounds comparable to plugging a USB cable into a human brain with a laptop and accessing brain information. However, it is not as simple as it sounds. BCI is a multidisciplinary discipline with an exponential progress parallel to and with Artificial Intelligence for the past decades. Initially started with the Electroencephalography (EEG) analysis, BCI offers practical applications for cortical physiology today. Although BCI outcomes are more perceptible in medicine such as cognitive assessment, neurofeedback, and neuroprosthetic implants, it opens up amazing avenues for the business community through machine learning and robotics. Thought-to-text is one example of a hot topic in BCI. So, it is quite predictable to see BCI for individual usage given the current affordability of platforms for less technologically savvy users as well as BCI integrated within office automation productivity tools. The current trend is towards vulgarization for businesses benefits, by extension to the society at large. Thus, the interest in preparing a book on BCI. This book aims to compile and disseminate the latest research findings and best practices on how BCI is expanding the frontiers of knowledge in clinical practices, on the brain itself, and the underlying technologies.

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