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Principles, Algorithms and Applications

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COGNITIVE AND COMPUTATIONAL NEUROSCIENCE - PRINCIPLES, ALGORITHMS AND APPLICATIONS

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Contributors

Seyyed Abed Hosseini, Luz Maria Alonso-Valerdi, Andres Antonio Gonzalez-Garrido, Hector Gomez, Andrés Espinal, Horacio Rostro-Gonzalez, Marco Sotelo-Figueroa, Héctor Javier Estrada-García, Manuel Ornelas-Rodríguez, Daya Shankar Gupta, Silmar Teixeira, Remigiusz Szczepanowski, Janusz Sobecki, Krzysztof Arent, Małgorzata Gakis

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Meet the editor

Dr. Seyyed Abed Hosseini received his BSc and MSc degrees in Electrical Engineering and Biomedical Engineering in 2006 and 2009, respectively. He received his PhD degree in Electrical Engineering from the Ferdowsi University of Mashhad, Iran, in 2016. He has 10 years of teaching experience and 1 year of industry experience. He has published over 55 peer-reviewed articles and book chapters in the field of emotion and attention studies. He is a lecturer at the Research Center of Biomedical Engineering (RCBME), Islamic Azad University, Mashhad Branch, Iran. He is a senior researcher at the Center of Excellence on Soft Computing and Intelligent Information Processing (SCIIP), Iran. His research interests include cognitive neuroscience, electroencephalography (EEG) studies, magnetoencephalography (MEG) studies, functional magnetic resonance imaging (fMRI), event-related potential (ERP) signals, emotion recognition, seizure detection, seizure prediction, brain-computer interface (BCI), and neurofeedback. The book "Cognitive and Computational Neuroscience - Principles, Algorithms and Applications" attempts to introduce the different soft computing approaches and technologies for identification of different brain states, from a historical development, focusing particularly on the recent development of the field and its specialization within neuropsychology, cognitive science, neuroscience, and engineering.

Contents

Preface

Neuroscience is a discipline that employs the tools and language of anatomy, linguistics, physiology, biochemistry, pharmacology, neurology, molecular biology, philosophy, biomedical engineering, psychology, and psychiatry. *Cognitive neuroscience* relates cognitive and behavioral functions to the underlying brain mechanisms. *Computational neuroscience* uses data to construct rigorous computational or mathematical models of brain function. Put them together, these new disciplines are the key to explaining the relationship between the brain and the behavior. The level for considering the cognitive and computational neuroscience is characterized by three main research lines: (1) microscopic scale - the activity and function of a single nerve; (2) mesoscopic scale - the activity of a local group of nerves; and (3) macroscopic scale - tissues, organs, organ system, and organism.

The cognitive and computational neuroscience research profile of this project is characterized by four main research lines: (1) language and communication; (2) perception, cognition, reasoning, action, and control mechanism; (3) memory and plasticity; and (4) brain networks and neuronal communication. The project was undertaken at the request of IntechOpen. During this period of intensive efforts, all the chapters were reviewed and revised accordingly to meet the high-quality standards of IntechOpen and my vision for the whole concept of the chapters.

This book will provide the audiences with the most recent evidence from different disciplines in brain studies on the wide range of researchers in an integrative way toward *Cognitive and Computational Neuroscience - Principles, Algorithms, and Applications*. The hope is that the information provided in this book will trigger new researches that will help to connect basic neuroscience to clinical medicine.

I would like to thank Ms. Marijana Francetic for her valuable comments and suggestions to improve the quality of this book. I would also like to thank all the authors, without whose cooperation I would not have been able to conduct this analysis.

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I hope you enjoy your reading.

Dr. Seyyed Abed Hosseini
Ferdowsi University of Mashhad
Mashhad, Iran

Chapter 1

Introductory Chapter: Cognitive and Computational Neuroscience - Principles, Algorithms, and Applications

Seyyed Abed Hosseini

Additional information is available at the end of the chapter

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1. Cognitive and computational neuroscience: principles, algorithms, and applications

The term "computational neuroscience" was introduced by Schwartz [1] through the organization of a conference in California in 1985. Cognitive and computational neuroscience evaluates the different brain functions (e.g., attention, emotion, perception, learning, consciousness, anesthesia, cognition, and memory) in terms of the information processing procedure of the brain [2]. This topic is an interdisciplinary issue that links the diverse backgrounds of neuroscience, cognitive science, psychology, mathematics, biomedical engineering, computer science, robotics, and physics. Therefore, the main idea of this book is to present a general framework for the researchers from diverse fields.

2. Related works

Cognitive and computational neuroscience has many medical and engineering applications such as rehabilitation [3], psychology and psychiatric disorders (e.g., depression, chronic addiction, post-traumatic stress disorder, dementia, attention deficit hyperactivity disorder, and autism) [4], brain-computer interface [3, 5], human-computer interaction [6], neurofeedback [7, 8], marketing [9], robotic [10], and decision-making [11]. Research in cognitive and computational neuroscience is categorized into four main topics, including experimental neuroscience (e.g., electrophysiology, neuron, synapse, synaptic plasticity, memory, conditioning, learning, consciousness, vision, neuroimaging), theoretical neuroscience (e.g., models of neurons, single-neuron modeling, spiking networks, network dynamics, behaviors of the brain networks, mathematical models of the brain activity, sensory processing, connectivity analysis), dynamical systems (e.g., synchronization, oscillators, pattern formation, chaos), and computational intelligence (e.g., neural networks, graph theory, reinforcement learning, pattern recognition, evolutionary computation, information theory, statistics, and signal processing).

Suitable brain signals and images are usually used according to invasive or non-invasive acquisition techniques. Therefore, non-invasive techniques, such as electroencephalography (EEG) [12, 13], event-related potentials (ERPs) [14, 15], magnetoencephalography (MEG) [3, 16], functional magnetic resonance imaging (fMRI) [17], positron emission tomography (PET) [18], transcranial direct current stimulation (tDCS) [19], and transcranial magnetic stimulation (TMS) [20], are generally preferred.

This section presents a detailed discussion of previous related works on different methods based on epilepsy and seizure detection along with different machine-learning approaches. In one study, Hosseini et al. [21] proposed a qualitative and quantitative analysis of EEG signals for epileptic seizure recognition. Hosseini et al. [22] proposed an approach for seizure and epilepsy recognition using chaos analysis of EEG signals. Hosseini [23] proposed a hybrid method based on higher order spectra (HOS) for recognition of seizure and epilepsy using EEG and electrocorticography (ECOG) signals.

Several studies have been proposed for the presentation of functional models, conceptual models, bio-inspired frameworks, signal processing approaches, image processing approaches, and electrophysiology studies based on cognitive processes, including emotion, stress, and attention. In one study, Hosseini et al. [24, 25] proposed a labeling approach of EEG signals in emotional stress state using self-assessment and psychophysiological signals. Hosseini [26] and Hosseini et al. [27–29] presented an HOS approach for emotional stress detection using EEG signals. Hosseini et al. [30, 31] designed an emotion recognition system using entropy analysis of EEG signals. Hosseini et al. [32] proposed an improved model of the behavioral calcium channels in the hippocampus CA1 cells during stress.

In another study, Hosseini et al. [33] proposed an emotional stress recognition system using psychophysiological and EEG signals. Hosseini et al. [34] proposed different features including fractal dimension, wavelet coefficients, and Lempel-Ziv complexity of EEG signals for emotional stress recognition. Hosseini et al. [35] presented a cognitive and computational framework of brain activity during emotional stress. Hosseini et al. [36] presented a cognitive and computational framework of the brain activity in emotional stress state. Hosseini [37] proposed attention and emotion recognition systems based on biological images and signals. Hosseini and Naghibi [38] proposed a computationally improved model of brain activity in the visual attentional state. Hosseini proposed [39] a computationally bio-inspired model of brain activity in the selective attentional state and its application for estimating the depth of anesthesia.

This chapter attempts to introduce the different approaches, principles, applications, and theories in cognitive and computational neuroscience, from a historical development, focusing particularly on the recent development of the field and its specialization within psychology, computational neuroscience, and engineering.

Author details

Seyyed Abed Hosseini

Address all correspondence to: hosseyni@mshdiau.ac.ir

Research Center of Biomedical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran

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Chapter 2

Convergence of Action, Reaction, and Perception via Neural Oscillations in Dynamic Interaction with External Surroundings

Daya Shankar Gupta and Silmar Teixeira

Additional information is available at the end of the chapter

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Abstract

There has been a considerable interest in the role of time-dimension in functions of the brain, which has been limited to time perception and timing of behavior. However, during past few years it has become increasingly clear that the role of the time-dimension includes other complex cognitive functions, such as motor control of a vehicle, sensory perception and processing imageries to name a few. Role of the accurate representation of time-dimension is important for several neural mechanisms, which include temporal coupling, coincidence detection, and processing of Shannon information. These mechanisms play key roles in processing information during the interaction of the brain with the physical surroundings.

Keywords: temporal processing of information, temporal coupling, time-dimension in the brain, neural clocks, timing behavior, muscle synergy, action-reaction

1. Introduction

Physical time-dimension is an integral part of information processing in the brain by virtue of its role in representing the information as a spike pattern on the time axis [1]. Accordingly, the final product of information processing taking place in the brain, such as perception, action, or interaction with external environment, is dependent on the accurate representation of time-dimension in neural circuits. The physical surroundings with which humans interact is four dimensional, three geometric dimensions, and the time-dimension. Psychological time has been a subject of intellectual curiosity for most of the known history, but time-dimension has been studied as the fourth physical dimension only during the last century [2, 3]. Time-dimension, unlike other physical qualities, is never perceived as a novelty but only reported as the flow of time [1], and therefore, it is not easy to study by observation alone.

Time-dimension plays a key role in many aspects of information processing in the brain. Temporal coupling of two or more events, neural or physical, occurs when they share the same coordinate on time-axis given that time-axis is represented accurately for all events. This allows the binding of events at the level of neural circuits or external physical surroundings. External events that are temporally coupled after processing in neural circuits lead to the subjective experience of entire repertoire of sensory inputs.

In coincidence detection, coincident activation of a third neuron by two oscillator circuits is proposed to play a role in analysis of frequency of auditory tones in the brain stem [4, 5]. The mental time travel is a fundamental ability of the human brain to "mentally" relocate oneself to a time point in the past or future [6]. The mental time travel allows the projection of self in past or future by referring a temporal order of events, which is processed by the hippocampus [7].

2. Interaction with external physical surroundings

Interval timing functions of the brain have arguably played a key role in the survival of the human species during most of their existence. Humans have been sustained by hunting and foraging [8], which requires interaction with external objects with a variety of physical characteristics, such speed, hardness, elasticity, and matter state—fluid or solid. These interactions are both (a) feedforward motor and (b) sensory—scene searching and sensory input. The feedforward motor control of external objects will be processed by sensory inputs resulting from reactional forces and impedance control (**Figure 3**). Mental time travel, by virtue of the

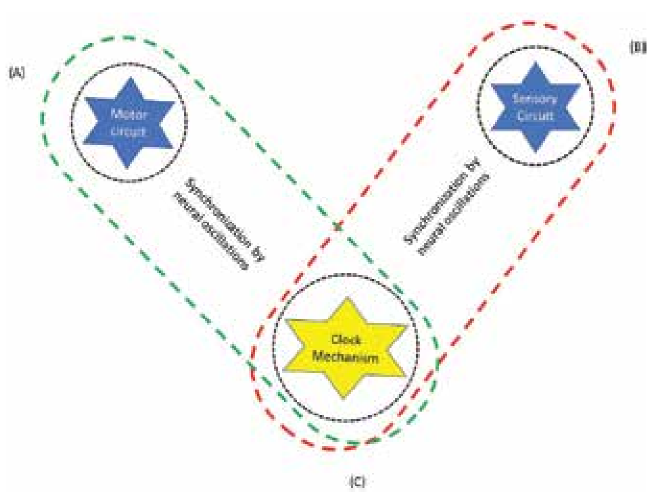

Figure 1. Depicts modular neural clock mechanism. Modular clock mechanism shown here is a prototype for the modular connections that form networks, processing information during interactions with external physical environment. The neural clock mechanism (C) can be synchronized with motor circuits (A) or sensory circuits (B) by low-frequency oscillations (broken rectangular lines).

ability to store the temporal order of events, helps to provide priors for the control of interaction with the environment as events unfold.

In addition, these activities require multiple temporal couplings of sensory inputs with motor responses at the level of a single individual. The use of limited energy stores by muscles must be optimized, which will constrain the central nervous system to recruit only certain muscle activation patterns.

Ability of individuals to communicate in groups, which is important for foraging, depends upon the temporal coupling of same brain circuits of different individuals to same stimuli, which may be hand gestures. Such brain circuits, found in the posterior parietal and motor areas, form mirror mechanisms in monkeys [9–11]. This is supported by imaging studies done in humans, which showed that the posterior parietal areas and premotor areas became active during action-observation and imitation [12, 13]. Moreover, rich reciprocal connections are present between different areas of the posterior parietal cortex and the premotor cortex in monkeys, which provide the anatomical basis of the mirror neuron mechanism [14, 15].

3. Representation of time-dimension in the brain

Representation of time unit by regular events is inherent in the definition of a regular event—that repeats itself after the same interval every time. Time units, such as seconds, measured by swings of pendulum in a mechanical clock, can help in the measurement of a duration by counting the number of seconds or swings of a pendulum. Using this analogy, a neural temporal unit is defined as the interval between two adjacent regular spikes, spike bursts, and is proposed to represent time units in neural circuits [16].

According to the pacemaker-accumulator model, when neural temporal units are added (or counted) by the accumulator, it processes neural time intervals for various subjective or motor tasks. According to this model, if the neural temporal units represented by neural oscillators in the brain's timing circuits are smaller on the physical time scale, then subjective time reported in the task will be greater than the elapsed physical time. This will be the result of a greater number of neural temporal units present within a given external time duration. As predicted by the pacemaker-accumulator model, a greater number of neural temporal units within a timed interval will lead to subjective overestimation of intervals. This is supported by a study in which entrainment using visual flickers with faster frequency increased time measurement in a time reproduction task [17]. Entrainment by faster flickers increases the frequency of neural oscillators in the brain, which leads to a smaller temporal unit—a result of entrainment by faster rate of oscillations. Another study used auditory click trains to increase the speed of neural clocks, and its effect on pair-wise duration comparison and verbal time estimation task, and had arrived at similar conclusions [18]. However, not all entrainment studies agree with this conclusion [19]. Thus, a different role of neural oscillator is suggested within the modular clock model [16]. According to this formulation, the role of rhythmic activity is to only represent a physical property of the time-dimension in various neural clock mechanisms. Rhythmic activities are shown to be important for cognitive functions and various forms of behavior as reviewed by Herbst and Landau [20], but its precise role is yet to be understood.

4. Modular connections of neural clocks: basis for timing functions

Modular model of distributed neural clocks is proposed by Gupta [16] for interval timing functions of the brain, such as timed motor movements, time reproduction, and time estimation. As depicted in the schematic in **Figure 1**, the proposed neural clock mechanism has three main modular components [16]: (1) calibration module, which is sensory and motor circuits of the brain that are involved in feedback interaction with the external four-dimensional surrounding; (2) endogenous neural oscillator to represent physical time in neural circuits; and (3) a clock mechanism for timing the behavioral response.

The functional role of the calibration module in the neural clock mechanism is to transfer information about the physical time from external surroundings into neural circuits. Physical time information is transferred into neural circuits when motor and sensory information is processed during an interaction of the brain with external surroundings. During the feedback process resulting from the interaction with physical surroundings, circuits associated with motor and sensory functions produce neuronal activities that parallel the interactions between effector organs, muscles, sensory organs, and external physical objects. A comparison of the intervals between changes external to the body and the intervals between corresponding feedback changes in neural activities in the brain is proposed to serve as a basis for the calibration of neural clocks.

Endogenous neural oscillator is the second component of the proposed modular neural clock mechanism. Neural oscillators are the rhythmic neural activities within the brain, such as neural oscillations, periodic bursts, or rhythmic circuits. The idea of neural oscillator to represent time-dimension is very old, which is based on the intuitive role of the pendulum in mechanical clocks. Treisman [21] had originally proposed pacemaker-accumulator model. According to this model, a neural oscillator generates pulses, which are accumulated by a counter to encode time intervals in neural circuits [22].

Instead of serving as the source for temporal units for pulse accumulation in the Treisman model, the endogenous neural oscillator in the modular clock mechanism only represents a property of physical time. Further, note that the periodicity of the endogenous oscillator does not simply represent a number that is added numerically to process time intervals for neural or psychological processes. However, as mentioned later, the numerical quantification of time intervals in neural processes is likely encoded by spike patterns and their temporal relationship. Neural oscillators, representing physical time, along with the calibration module and various task-specific circuits, synchronously generate information in networks, forming modular clock mechanism (**Figure 1**) to encode timed behavior.

Task-relevant neural clock is the third module, which is generally a part of local circuits, distributed across the central nervous system. For example, the neural timers for visual time reproduction tasks in seconds range are present in the right dorsolateral prefrontal cortex [23–25].

At present, it is not clear how neural patterns, representing information, are coded and decoded to result in behavior, such as timing movements or time estimation. It is likely that a combination of different patterns, such as spike patterns, logic states of neural circuits, ramping activity of neurons, are important for coding and decoding information, leading to timed behavioral responses [16].

Quantitative measurements, such as time intervals, are likely represented in neural circuits in numerical representations [26], such as spike patterns, which can be read as the binary numbers [1, 27]. Studies suggest that the information about behaviorally relevant quantities such as timing behavior is not represented by the rates of spikes but rather by the intervals between their arrivals at synapses [26]. Coincidental activation of neurons by two different sources in a periodicity analysis model is proposed by Langner and Bahmer [28] for analysis of auditory signals in the brain stem.

Although the neurobiological basis of information processing, underlying the timing of behavior, remains far from clear [26], some consensus is present, such as, neurons encode sensory information using a small number of active neurons, called sparse coding [29]. Independent activation of a small number of neurons is consistent with the cytoarchitectonic data that show a low level of connectivity among the neurons of the cortex.

5. Cytoarchitectural basis of modular connections

Modular connections of local circuits forming dynamic networks are supported by cytoarchitectural and electrophysiological data from the study of the cortex. The cerebral cortex is divided into tiny computational units of mm range size, called the canonical microcircuits [30]. The neurons forming the canonical microcircuits have limited but conserved patterns of inputs and outputs [31]. Although the neurons within a canonical microcircuit are interconnected in specific patterns, the connectivity rates between most neuron pairs in the cortex are very low, which are less than 10–20% in most cases [31]. Due to a low level of connectivity among neurons, different combinations of multiple canonical microcircuits can be configured into a large variety of neuronal circuits and, therefore, provide the ability to perform a wide variety of computations. This feature is particularly useful for the role of small areas of the cortex to act as relatively independent modules in neural networks.

Moreover, inputs relayed to the cortex are organized in spatial patterns. This, combined with a little direct interaction between the canonical circuits in horizontal direction, results in independence of small cortical areas, which allows small cortical areas to act as relatively independent local circuits or modules. Local circuits are interconnected by synchronization, processing information to allow the brain to interact with the external physical world. The synchronization of local circuits is due to the oscillating states of excitability and inhibition, which allows neurons to fire during a specific phase of a long-range oscillation when neurons are excitable—coupling the modules of a neural network [27, 32, 33]. Periodic excitability of neurons during synchronization, due to pacing by inhibitory neurons, produces oscillating extracellular currents that are recorded as neural oscillations [34], which show different patterns during different behaviors. The behavioral significance of synchronization is due to the temporal coupling of neural events that underlie action and perception.

6. Role of oscillations in the representation of time-dimension

Since the discovery of neural oscillations in electroencephalography (EEG) by Hans Berger at the University of Jena, our understanding about its importance in cognitive functions has grown exponentially. Theoretical consideration as well as experimental evidence suggests that time-dimension is represented in the central nervous system by rhythmic activity of neural oscillations [1, 16, 27]. The importance of neural oscillations in cognitive functions became known when synchronized neuronal firing pattern, which was tightly correlated with the phase and amplitude of an oscillatory local field potential in the cat visual cortex, was reported in 1989 by Gray and Singer [35]. Furthermore, the stimuli were correlated to the amplitude of the oscillatory field in specific neuron clusters [35]. Neural oscillations represent a common unit of physical time-dimension in information processing when they synchronize different parts of the brain into networks [27].

Accumulating body of evidence now suggests that beta-range neural oscillations represent physical time information in the brain [16, 19, 27, 36–40]. A recent study has concluded that beta oscillations play an important role in the retention and manipulation of time information held in working memory [37]. A causal relationship between beta oscillations and the control of movements [41] has been shown, which further suggests that beta oscillations are responsible for coupling the neural-timer mechanism with the motor circuits for the control of movements.

7. Representation of time-dimension in lower motor circuits

Central pattern generators (CPG) are networks of neurons in the spinal cord-forming oscillators that play a role in hierarchical control, generating rhythmic motor activities in animals, such as walking and chewing [42]. The rhythmic activity of CPG networks, according to the formulations of distributed modular clock mechanism, represents time-dimension in spinal cord motor circuits that help to control the temporal characteristics of locomotion. Although, CPG activity is observed after deafferentation or spinal cord injury, the sensory inputs, especially proprioceptive signals, are crucial for its role in locomotion [43]. The function of proprioceptive signals is likely the calibration of neural temporal units represented by rhythmic activity of the CPG [16].

The evidence for the direct role of spinal cord CPG networks in human locomotion is scant and is mostly indirect [44, 45]. Some beneficial effects are seen in spinal cord injury patients following locomotor training [46], which can be attributed in part to the plastic changes in spinal cord CPG networks following the training, which updates physical time-dimension information from sensory, especially proprioceptive inputs during training sessions [16].

8. Role of temporal coupling in information processing

Representation of time-dimension in the brain is important for human and nonhuman primates' ability to survive. As argued earlier, the representation of time-dimension in neural circuits plays a key role in the information processing underlying complex cognitive functions of the primate brain. Survival in many circumstances depends on the temporal coupling of action with the perception during the interaction with the external physical surroundings.

Depending upon the demands of a task, such as speed, the cost of failure, and the degree of coupling between action and perception, may vary. To couple feedforward motor output with sensory inputs on a small temporal scale, a more accurate representation of time information in neural circuits is required.

9. Role of coincidence detection in information processing

Coincidence detection refers to occurrence of an event only when two or more events take place synchronously. Oscillations are hypothesized to play a role in decoding the temporal information in ramping neuronal activities [16] that are commonly observed in the cortex [47–50]. Coincidence detection would play a role in generating the information that produces timed behavior. This information is processed when coincidence detector neuron is stimulated by both excitatory presynaptic terminals controlled by gamma oscillations [51] and an increasing excitatory input coming from a ramping neuronal activity (**Figure 2**). This

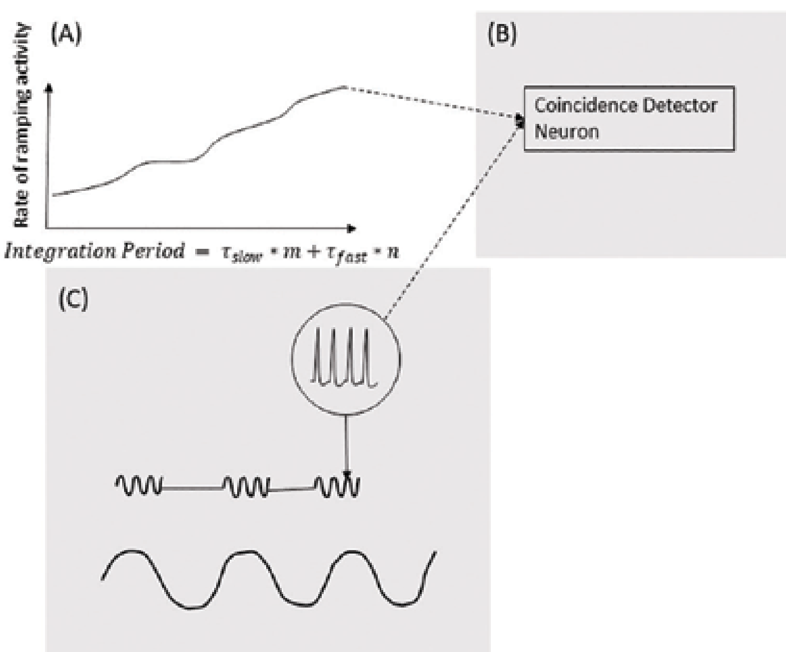

Figure 2. This figure shows how coincidence activation can result in the analysis of temporal information represented by neuronal ramping activities, commonly observed in the cortex. The ramping neuronal activity provides an increasing input to neuron that is synchronized by a high frequency nested within a low frequency (C). The neuron synchronized by (C) is excited by high frequency (periodicity is τ_{high}) gamma oscillations, within a specific phase of low frequency oscillation (periodicity is τ_{low}). The excitation of neuron (B) will result in an activity (coincidence detection), if there are three simultaneous events (1) input from neuron with climbing output (A) after reaching a particular level of activity (2) phase of long-range oscillations that allows gamma cycles (3) excitatory phase of gamma cycles. Thus, the integration period resulting from coincidence analysis will be represented by the formula shown within the figure, where m and n are integers.

coincidence detection model is based on the periodicity analyzing model for auditory signals in the brain stem proposed by Langner and Bahmer [28].

10. Input of time-dimension during the Cochlear processing contributes to sound perception

Psychoacoustical studies have indicated that perception of speech is not adequately accounted by place frequency mechanisms [52]. But the temporal information represented in sounds is also important in the perception of speech [52]. Therefore, it noteworthy that recent theoretical work and a growing number of experimental studies indicate that time-dimension is an integral part of information processing underlying perceptual functions of the cortex [16, 27].

Most natural sounds are modulated in amplitude, which can be explained by a mixture of sound waves of slightly different frequencies producing destructive interference near the tails and summation near the peak in the center [53, 54]. Thus, time-dimension is represented by the modulation frequency in addition to fine oscillations of air pressures causing sound waves. The oscillations of both frequencies, forming the structure of natural sounds, represent physical time-dimension [16]. The processing of sound waves by the cochlea produces amplitude modulation (AM) signals in the brain stem. The spike structure of AM signals is phase locked to changes in pressure produced by amplitude-modulated sound waves during the transduction by the cochlea. Studies also suggest the presence of tonotopic organization of subpopulations of neurons tuned to modulation frequencies [53], consistent with the transduction of time information in modulated sound waves, which is later processed in the auditory cortical areas contributing to perceptual qualities of sound.

11. Role of time-dimension in movements

11.1. What are muscle synergies?

Muscle synergies represent the central nervous system's response to the redundancy problem in motor movements. There are many more degrees of movements possible than are the number of muscle activation patterns that can produce movements [55, 56]. Several studies in vertebrates and non-vertebrates demonstrate the presence of elements or muscle synergies, from which complex patterns of motor movements can be constructed [56–58].

11.2. Computational models of muscle synergies

According to the computational models of muscle synergy, a synergy can be described as a D-dimensional vector field, where D is the number of muscles involved in movements [59, 60]. The level of contraction of each muscle, represented by weighting coefficient (Wi) multiplied by a coefficient (Ci) to yield (Ci(t)Wi), represents one of the dimensions. The level of contraction (Coefficient*W, W is the weight of contraction) is referred to as synergy in the following computational models of synergy. The synergies are extracted using non-negative matrix factorization of EMG patterns. Prior to the analysis, EMG data is adjusted by subtracting the tonic component of EMG activity responsible for postural activity and balance [60] or by normalizing EMG data as discussed earlier [61].

The maximum number of dimensions (D) in muscle synergies after extraction is the number (D) of all muscles that could play a role in the movement. After the extraction of muscle synergies from EMG patterns, the minimum number (N) of synergies is computed, such that they account for 80–90% of variability of the movements by choosing either coefficient of determination (CD) or variability accounted for (VAF) criteria. It has been observed that a small number of extracted muscle synergies can account for most of the variability of movements, while others account for 10–20% of the variability [59]. This provides a solution to the redundancy problem: few patterns of movements are preferred over far larger number of possible movements.

11.2.1. Spatial or time-invariant synergy model

$$m(t) = \sum_{i=1}^{N} Ci(t)Wi \tag{1}$$

In time-invariant synergy, there is a fixed level of contractions (weights) of muscles (M_1, M_2… M_n)—W_i for ith synergy. Each time-invariant ith synergy is activated by the nervous system temporally, represented by a time-varying coefficient (Ci(t) for ith synergy at time t). In this muscle (ith) synergy, fixed weights of contraction of muscles are multiplied by a time-varying non-negative coefficient Ci to obtain muscle activation contributed by each synergy (Wi) [58]. Time invariant or spatial synergies can be described at a more abstract level as the uniform modulation of a D-dimensional vector field wherein the amplitude of the vector is the fixed levels of contraction of individual muscles.

11.2.2. Time-varying synergy model

$$m\langle t\rangle = \sum_{i=1}^{N} CiW(t - ti) \tag{2}$$

In time-varying synergy, there are multiple waveforms corresponding to muscle contractions or vector amplitudes of individual synergies. Synchronous contraction waveforms of different muscles are multiplied by the same coefficient (Ci) for the ith synergy and shifted in time by a delay t_i and added to generate muscle activity pattern [59].

11.3. Recruitment of muscle synergies: a computational strategy by the brain to optimize motor movements within the constraints of musculoskeletal system, energy cost, and external physical surroundings

The computational models of muscle synergies reveal the modular control of muscles during movements. The muscle synergy recruitment in computational model can be explained by two orthogonal components. The spatial synergy model (Eq. 1) suggests that signals originating from a cortical circuit (from convergent to divergent) (defined as type I) control multiple muscles by sending sending signals of different strengths to different muscle with a fixed amplitude relationship between them, while another circuit (defined as type II) modulates the activity of type I circuits, producing a time-varying modulation of fixed levels of muscle contractions constrained by the amplitude relationship, reflecting the spatial demands of the task. During a movement, synergies are recruited by sending signals from type II circuits to type I circuits. When several synergies (Wi) (type I circuit) are recruited by several corresponding sources of time-varying signals (type II circuit), it leads to the movement to be constructed by a computational mechanism. The orthogonal components of spatial synergies are detected by decomposing EMG patterns.

The type II circuits, which produce time-varying signals, represent time-dimension in the information processing that underlies the control of movements. Due to the representation of time-dimension, type II circuits are likely to be controlled by dynamic inputs, such as speed and temporal coupling. Type I circuits are responsible for representing the spatial directions of movements. Muscle contractions represented by type I circuit will determine the set of conditions, representing limb and joint positions for specific directions required for external task conditions. Furthermore, types I and II circuits are orthogonal or statistically independent, which is suggested by the decomposition of EMG patterns by the matrix factorization.

It is noteworthy that movements in humans are smooth. This suggests that muscles are not controlled individually by independent feedback processes, which would increase variations between contraction states of individual muscles, thereby decreasing the smoothness of movements. Instead, the muscles in each spatial synergy is controlled by a single signal (represented by time-varying coefficient in Eq. 1), which helps to reduce the number of variables being controlled, leading to an overall reduction in variations within movements. Thus, muscle synergies represent simpler computational solutions implemented by the central nervous system for controlling movements. Moreover, only a limited number of synergies can be recruited within the constraints of musculoskeletal system.

11.4. Control of muscle synergy recruitment

According to the classical view of the control of reaching movements to catch a ball, there is a creation of a neural representation of endpoint of the task, such as the hand meeting the ball in the physical space to execute a catch [62, 63]. This neural representation is formed by an initial approximation, which then evolves temporally [63]. The motor movements are produced by recruiting a limited number of synergies by the central nervous system, which can be directed by the neural representation of the prospective endpoint of the task. State estimators, which are discussed later, play a key role in optimum feedback control as it would predict the neural representation of the endpoint. The time-varying coefficient represents the time-dimension in the information processing movements, as it is modulated with time. Thus, time-varying signal (Ci) helps to determine the speed of movement, while the other orthogonal component, muscle synergies, is a response to spatial and musculoskeletal constraints.

Temporo-parietal cortical areas are believed to play a significant role in the feedback processes that help to represent the musculoskeletal system in the external four-dimensional environment [64, 65]. Studies of the computational models of muscle synergies indicate that the nervous system recruits a limited number of synergies that optimizes according to a temporally evolving map of the neural representation of the hand meeting the ball. Recruitment of muscle synergies is also due to the numerous specific, reciprocal connections between the regions of the parietal cortical areas and frontal motor areas [66]. These specific multiple, reciprocal connections may form the basis for the recruitment of muscle synergies as well as the temporally evolving map of the neural representation of the map of the endpoint of the task. Furthermore, it is likely that the direct effect of state estimator module of the optimum feedback control is on the neural representation of the endpoint of the task rather than on muscle activities. The muscles are controlled from frontal motor areas, which are functionally connected to temporo-parietal areas where the multimodal integration of sensory information—proprioceptive, vestibular, and visual—takes place [64, 65].

11.5. Optimum feedback control theory

Although motor movements in humans are smooth, but the motor performance shows a large variability from trial to trial. This large variability in the movements is a reflection of inherent noise in the motor circuits, also called signal generated noise, in addition to the noise present in sensory circuits, and the external source of sensory inputs. Optimum feedback control is used by the central nervous system to modify feedback signal to control some index of motor function, such as minimization of endpoint errors or achieving a maximum jump. The control of motor outcome is optimum when it meets the spatiotemporal constraints of a task, such as hand meeting a ball during a catch. As a result, there is a decrease in the variations along the trajectory of the task; however, this is accompanied by the increase in variations in task-irrelevant trajectories. State estimator functions provide outputs to the feedback controller which helps to produce the optimum outcome [67].

A modification of optimum feedback control would consider the feedforward motor output via synergy recruitment. State estimator would recruit a limited number of muscle synergies that would account for 80–90% of variability of the movements according to VAF or CD criteria. The mechanism to explain the control of the recruitment of synergies must take into the constraints that limit movements. Muscle contraction velocity profiles, due to the constraints of viscoelastic properties as well as the biochemical events underlying sliding filament mechanism, are bell-shaped. The allowed muscle contractions must minimize the energy cost in the use of skeletal muscles, which is imposed as inheritable features on neural circuits due to evolutionary pressures. Furthermore, only certain movements are allowed by the joints, which depend on various factors, such as the shape and the structure of joints. The function of state estimator depends upon sensory inputs and efferent copy of cortical motor commands, which provides estimation of online changes occurring in the state of the musculoskeletal system [67].

Please note that sensory inputs and efferent copies of motor commands must be integrated with time-dimension in order to serve as state estimator for the optimum control of motor movements via synergy recruitment. The early online control of movements likely involves the integration of unimodal sensory state estimates instead of a single multimodal state estimate [68]. Studies have shown that during reaching movement task, joint angle variability peaked mid-way during the task [69], but there is a high accuracy at the endpoint [70], which suggests optimum feedback control of movements.

Optimum feedback control depends on a set of distributed circuits, among which the primary motor cortex appears to play a key role. It has been shown that the primary motor cortex receives inputs from several brain areas, which include the premotor cortex, primary somatosensory cortex, posterior parietal cortex, and pathways via the thalamus from the cerebellum, forming some of the structures involved in optimum feedback control. A recent study also shows that if feedback controller is represented in the primary motor cortex, the optimum feedback control describes multiple representation of preferred directions of torque or movements in which muscles are most active [71]. This is consistent with the role of the primary motor cortex as the site where individual synergies, involved in constructing voluntary movements, are recruited by the activation of individual spatial synergies by time-varying signals.

12. Controlling a motor vehicle: a special case of convergence of action, reaction, and perception

Newton's third law of motion states that for every action, there is an equal and opposite reaction. Newton's third law can be applied to analyze the interaction of the brain with the four-dimensional physical surroundings. The action, which results from movements, produces the reactional forces on the human body, resulting in changes in the activity of mechanoreceptors, which then modifies the activity of the musculoskeletal system responsible for movements in a feedback process. Thus, pairs of forces, action, and reaction forces during interaction between primates and their environment lead to changes in the activities of sensory and motor functions of the brain via feedback processes. In addition, successful interaction between the brain and the external environment depends on several other factors, which includes the representation of time and spatial dimensions in neural circuits of the brain. During this interaction, there is a complex interplay between feedforward motor process and sensory inputs. An important example of such a complex interaction is a driver controlling a motor vehicle (**Figure 3**). The control of the vehicle involved is due to two main motor actions, pressing the gas pedal to change the speed of the vehicle and the steering wheel to change the direction. The motor control of the vehicle, which is the feedforward motor prediction based on internally generated top-down feedforward output, is directed by a negative feedback process involving sensory inputs of different modalities.

Visual input, after processing in the posterior parietal cortex, is relayed to the primary motor cortex, which will be important for the control of movements with the help of visual cues. The premotor cortex is involved with the planning of movements and the internally generated signals, while the primary somatosensory cortex plays a role in processing inputs related to the perturbations of musculoskeletal system during movements.

Scene processing involves recognizing the environment, searching the information in the environment, and navigating through the environment [72]. Visual scene-selective regions are occipital place area, parahippocampal place area, and retrosplenial complex, which are on the lateral occipital, ventral temporal, and medial parietal cortical surfaces, respectively [72, 73]. Parahippocampal place area is believed to reflect a wide range of properties, such as spatial

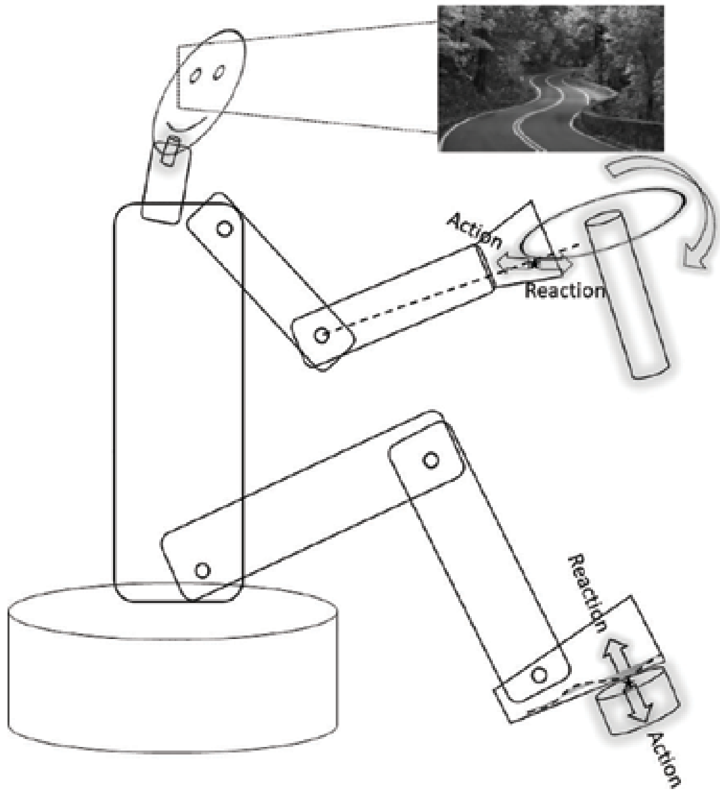

Figure 3. It depicts the interaction between feedforward motor output and feedback sensory input resulting from the stimulation of proprioceptors by reactional forces acting on the foot and hand. Visual information from the scene is actively gathered to provide additional but crucial sensory input.

frequency, orientation, texture, object identity, as well as size of a space [72]. A recent study has shown that the networking of the visual cortex with retrosplenial cortex is important for mental time travel, which would play a role in constructing prospective scenes [74], such as seeing an increasing number of brake lights will suggest a slowing traffic. The self-projection in time, called mental time travel, relies on various neural structures, encoding memory, mental imagery, and self, which is critical for the judgments during interactions with the physical environment [6]. Mental time travel recruits a network, which includes the anteromedial temporal, posterior parietal, inferior frontal, temporo-parietal, and insular cortices [6].

13. Biochemical and genetic basis of inter-individual variations in timing functions

A recent study of review-based evidence, which examined a large number of studies, suggests a key role of the dopaminergic system in various temporal functions of the brain [75]. These conclusions are based on various combinations of genetic, pharmacological, physiological, and psychophysical evidence [75]. This review suggests an important role of certain key molecules, which influence the concentration of synaptic dopamine, in various timing functions of the brain. These molecules includes catechol-O-methyltransferase (COMT) that degrades synaptic dopamine and dopamine transporter (DAT), which removes dopamine from the synaptic cleft. Studies of common gene polymorphisms, COMT gene (COMT Val158Met) and DAT gene (SLC6A3 3'-VNTR variant), suggest the involvement of dopaminergic system in time perception.

Study of the effects of dopamine agonists, such as cocaine and metamphetamine and dopamine antagonists, haloperidol, on peak interval task suggests that both attentional and clock mechanisms are dependent on dopaminergic neurotransmission to some extent [76]. As argued earlier, cognitive functions are functionally dependent on timing as time-dimension is a part of the physical environment with which the brain interacts. In addition, neural oscillations, which represent time-dimension in neural circuits [16], help to form networks that form the basis of perception and action coupling [27]. Thus, we propose that dopaminergic system is one of the main chemical bases of timing circuits. This is consistent with the anatomical evidence, showing the extensive presence of dopamine terminals in layer I, with more specific presence in deeper cortical layers V and VI, which has neurons, projecting to the thalamus and striatum [77]. Dopamine can also play roles in the maintenance of homeostasis of neural circuits via cortico-striatal-thalamic-cortical loops [16]. This is consistent with the importance of dopaminergic system in cognitive and timing functions [78]. This view is further supported by the well-known role played by abnormal dopaminergic system in schizophrenia, which is a disorder of cognitive functions and time perception. Furthermore, the genetic variations in expression of molecules related to dopaminergic system in the brain are likely to contribute significantly to the variations in timing and cognitive functions between individuals.

14. Conclusion

Time-dimension plays a key role in all aspects of the brain functions. However, the focus study of time-dimension has been on a limited number of functions, which include timing behavior, subjective time perception, and temporal order. In this book chapter, we have extended the importance of time-dimension in the study of other aspects, such as movements, perception, and highlighted the importance of temporal coupling of neural and physical events during the interaction with external environment.

Author details

Daya Shankar Gupta[1]* and Silmar Teixeira[2]

*Address all correspondence to: dayagup@gmail.com

1 Department of Biology, Camden County College, Blackwood, NJ, USA

2 Brain Mapping and Plasticity Laboratory, Federal University of Piauí (UFPI), Parnaíba, Brazil

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Chapter 3

Cognitive and Computational Neuroscience: Principles, Algorithms, and Applications in Surveillance Context

Lozada Torres Edwin Fabricio,
Martínez Campaña Carlos Eduardo and
Gómez Alvarado Héctor Fernando

Additional information is available at the end of the chapter

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Abstract

Today, working with human behavior is vitally important, especially if we consider the impact neuroscience and security systems. The responsibility of monitoring in a conventional way is in charge of a human agent (vigilant). On the other hand, a vigilant cannot be aware at all times. He can only be aware for 20 minutes which is the time he can monitor four cameras simultaneously; after that, the task of surveillance ceases to make sense. This reveals one of the shortcomings of surveillance (SV) systems. Whether a surveillance system provides a warning of an activity or situation makes it as important as the selection of the technological elements that allowed it to be captured. Security systems based on intelligent technologies have had an accelerated development in recent times detection and identification of car registration numbers, detection of static objects in tracks, and detection of pedestrians circulating on not permitted routes. The reuse of methodologies, procedures, and ontologies is described in this chapter of the book.

Keywords: cognitive, surveillance, applications, algorithms, behavior

1. Introduction

The analyst of sequences of video is a very important topic at the time of using this strategy for surveillance of security places. The problem consists in understand any success of the real life saved in a video camera; this process for recognized persons, objects, vehicles, danger places, alarms, etc. is the principal goal of this work [1]. Use the term monitoring to conceptualize the process of collection and selection of activities according to the relevance of the situation that needs to be identified. This process is part from the monitoring of signals or images that allow characterization of the situation of interest. Thus, the general objective of this monitoring is to identify suspicious situations in order to ensure that activities and situations are normal, so it informs about possible abnormalities that may occur [2].

Ubiquitous computing also supports the development of surveillance (SV) systems through the recognition of activities of the high semantic level based on multisensory monitoring which goes from the capture to the interpretation of the signal. Through the different stages, the abstracted information provided by the sensors is associated with the activities that happen on the stage—person watching television, person takes their medicine, and person calls by phone. In general, this type of multisensory recognition has been applied to infer activities of people's daily lives [3]. The analysis of multisensory information requires a high degree of abstraction from the low semantic level that does not produce the necessary details to understand the detail of what happened in a scenario. This semantic gap is clearly identified in SV systems that process multisensory signals as they pass directly from the sensory signal to interpret the situation. This interpretation always depends on the knowledge, the expression capacity, and the specific language of the scorer. Some researches propose solutions to eliminate the semantic gap. Most of them are based on structures that start from the low semantic level to obtain a high level that allows quality descriptions that help in search and recovery of activities and situations in the SV systems [4, 5]. In the next subchapter, we explain the solutions to SV based on cognitive neurosciences.

2. Symda project

In spite of all the research efforts, it has not been possible to integrate the SV systems in a single functional structure. This is an idea that would allow improvements in the interpretation of situations in a scenario. There are architectures that group multisensory systems in order to help the human operator to make decisions according to identifying a situation of interest, a theme must be developed from the technological combination. With this topic the SIMDA group has carried out projects that propose the integration of different technologies and the semantic conceptualization of situations [4]: AVANZA, CICYT 2004, CYCYT 2007, and INT3. The contribution of INT3 is fundamental to this work, as they obtained from Horus, a multisensory framework for monitoring and detecting activities, integrating multisensory systems into a single processing unit, as shown in **Figure 1**.

As shown in **Figure 1**, Horus is a modular architecture for management of multisensory inputs, incorporating a model of conceptualization that allows sharing information of interest among multiple scenarios. Multisensitive sources are mainly related to image sensors, since they are the most widespread for monitoring tasks although other technological sensors, such as wireless sensor networks (WSN), are also integrated into INT3-Horus generic objects. The framework is distributed and hybrid. The remote nodes perform not only the lower level processing but also data acquisition, while a central node is responsible for collecting the information and its coalescence. The proposal consists in the identification of things and the monitoring of human behavior [5]. This is eminently complex since there are multiple objects and types of behavior. The model has input and output interfaces, which allow reuse

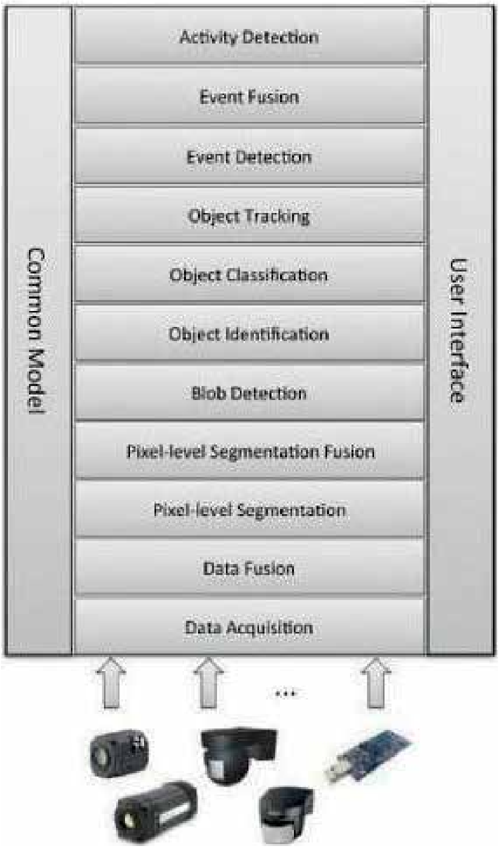

Figure 1. Horus modular system (Source: Castillo et al. (2012)).

and adaptability, all based on the security model in video surveillance systems. For this it is necessary to obtain elements such as entities, procedures, and the relationships between them. In event-based systems, the MVC provides information about changes in the application and provides a representation that adapts to the needs of the user. The model receives inputs to the application and interacts with it to update the objects and to represent the new information [5]. We propose to work with knowledge structures, which collect generalities and particularities of the situations of interest in order to automatically identify them in the monitored scenarios [6, 7]. During the last decade, the ontologies are used in applications for the areas of natural language processing, e-commerce, intelligent information integration, information consultation, database integration, bioinformatics, education, and semantic web, among others. These ontologies provide a vocabulary and organization of concepts that represent a conceptual framework for the analysis, discussion, or consultation of information from a scenario. But, there is a need to perform reasoning tasks which modules or tools must be integrated into a single conceptual, methodological, and technological framework. These modules must be coupled to Horus framework, in order to infer activities of the high semantic level (see **Figure 2**).

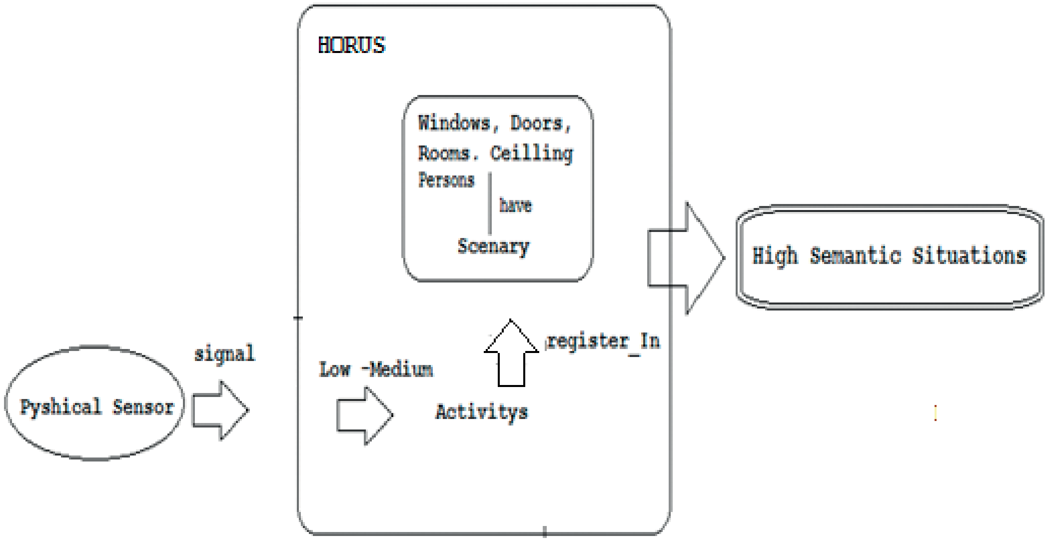

Figure 2. Semantic model: the knowledge structure is used to model scenarios, activities, and situations.

The hypothesis to be verified is that, through the design of ontologies and semantic technologies easy to use, reuse and modulate it can inferre situations of high semantic level and the rapid prototype of SV systems with a similar level of abstraction that a human agent has. To verify our hypothesis, ontology must fulfill the following aspects:

1. It is a semantic multisensory referential framework, which reduces the difficulty of working with different types of signals from different sensors that together with the semantic conceptualization of the signal allows to obtain the latest in the appropriate characteristics of the behaviors and activities developed in the context under study.
2. Systems based on ontologies conceptualize the information that comes from the case in the investigation. Applying this theory to video surveillance systems, it is possible through semantics to infer and have retrospective analysis, that is, perform the activities even after they have occurred.
3. Import ontologies. It adapts its structure to be combined with other ontologies developed in different domains. This is in order to reuse representations of knowledge in different areas of science.
4. Conceptualize and infer activities. It is the process in which the knowledge of the expert is used to conceptualize activities, or rules or axioms for inference are applied to the activities that are recorded in the scenario. We are tasked with inferring activities of the medium and high semantic level, while Horus is tasked with the low semantic level.
5. Conceptualize and infer situations. It is to allow the vigilant or expert to establish the relationships between the activities that happen in it and to design rules and semantic axioms

to infer a situation. In an alternate way, it is to have the semantic capacity needed to adapt its structure to the appearance of new conceptualizations of activities and situations as a product of learning acquired by computer algorithms. Based on the interest of knowledge situations, there are two types of tasks: (a) conceptualize and model the knowledge of the human expert, when it exists (depending on the basic activities recognizable from the sensors or the processing of video images), and (b) conceptualize and model situations where the knowledge does not exist although it is possible to find it in records (case bases) of the situations that are intended to be identified. In this case, the required process is particularly complex [8, 9], and it will require the use of intelligent algorithms for identification. Literals (a) and (b) are studied in this research, since we work with the knowledge of the expert when he can clearly describe the scenarios and situations, in addition to scenarios where there is some expert knowledge which is not precise and is intended to find automatically the situations of interest. Here, situations are composed for activities that individually are not clearly suspicious, but when analyzed in a certain sequence and repetition, they do reflect to be.

The use of SV systems based on closed-circuit television (CCTV) cameras has grown exponentially over the last decade. Especially, concern for security as a result of emerging international terrorism has led experts to anticipate a greater diffusion of these systems as well as their integration into a global remote monitoring network [10]. Analyzes the latest advances in the multisensory SV systems use by companies that produce this type of technology with an emphasis on their manufacturing, added value, other products differences, and its use. This analysis focuses on the SV systems based on cameras and sensors for surveillance. The result of the analysis allows answers to questions such as the following: Would it be useful to be able to track people in different areas and places? Is it possible to check for false alarms in establishments or simply monitor a trade from the comfort of home?

Applications of this type are already commercially available, allowing access from a single control center to images of CCTV systems in various geographically distributed environments. For example, the synchronized video acquisition system is developed to interoperate with SV systems in order to act as an object trajectory server. It consists of a series of navigational instruments that allow the direct geo-referencing of each of the images captured by the video camera in post-processing in a common reference time for all navigation instruments and for all sensors used in the capture system video. Remote sensing allows to have information about an object or surface through the analysis and processing of the data supplied by different sensors that are synchronized. In addition, it associates the time and Global Positioning System (GPS) with the image generated by the video [7]. As a result systems are capable of analyzing the video of different subsystems and interpreting what happens in the images. Applications of examples that can have video acquisition and synchronization systems are real-time monitoring of traffic conditions, forest fire control, natural disaster monitoring, and geo-referenced video projection in public virtual machines such as Google Earth and Virtual Visualizations [7].

3. Ontology and agents

Analyze surveillance system based on cameras which have been done by using three different methods: the first one has been developed using an expert knowledge, the second one was learned from recorded videos, and the third one has been developed as a refinement taking into account evaluation with ground truth. This project was deployed in Madrid-Barajas airport; this technology is used to support ground traffic management inside the Advanced Surface Movement. Model-Based Reasoning (MBR) modeling of semantic reasoning allows the resolution of problems in the identification of activities in space and time. This is a basic theme of the same, since the temporal management must be strictly linked to the occurrence of the facts. However, there are still two fundamental problems in this application: the degree of dependency between the model use and the domain and the reutilization on the systems when the domains change. The implementation aim is to help solving the problem of temporal diagnosis for environments of high conceptual complexity integrating MBR and ontologies for domain knowledge representation. A traditional system of security and vigilance is that the caretaker is alert toward what happens in the zone which needs security. In this kind of system, the quality of the vigilance has a direct relationship with the human capacities of the caretaker, which are incremented with the use of security cameras, motion sensors, etc. A minimum requirement for security systems is the ability to analyze multiple objects or groups of objects in real time [8, 11]. The main objective of this study is to calculate some parameters for the performance evaluation of the tracking system in order to identify an alarm human behavior. Here, it is necessary—the problem—to consider a sequence of previously recorded videos as well as subsequent processes in which a human operator takes notes of the images and places marked on each video frame. Using ontology with agents for running the system, we proposed the next system (**Figure 3**).

The first step only uses the two classes in the CARETAKER ONTOLOGY (**Figure 2**), person and objects, to determinate how the system function and learn from this. Without using the speak recognition and write recognition (see Crubèzy, Connor, Buckeridge, Pincus, Musen: Ontology-Centered Syndromic Surveillance for Bioterrorism.), the structure is similar at the bioterrorism ontology (**Figure 4**).

The CARETAKER ONTOLOGY has other classes and properties (**Figure 5**).

Now, in this job selection, the classes are person and object. To use these classes, it is necessary that the image catcher for the sensors at the office can be s processed to recognize people, objects, and activities. In CARETAKER it is possible to see these elements for the ontology (see A Real-Time Scene Understanding System for Airport Apron Monitoring: AVITRACK Project): the AVITRACK project has the same structure for the ontology.

Scene analysis terminology:

Scene: Place of development of activities, events, and activities.

Physical object and interest: Thing in tracking or tracking that is in the study area. These objects allow their relationship to obtain the contextual object, since this occurs after the relationship between physical objects. The movement of this type of objects can be random and unprovoked.

Contextual object: The object of a scene conditioned to the appearance of activities, events, and activities.

Objective tracked: The object of interest located in the area of interest, directly related to semantic tracking.

ROI: Region of interest. The context, area, or region of interest.

Oscillating movement: Constant movement related to the fact, it can be provoked or not.

After this work using the CAREGIVER:

We have proposed the syntax to describe states, events, and activities. These meta-concepts are described with a name and four parts:

Physical objects: Semantically related produce facts.

Components: What allows to obtain a description of a context.

Prohibited components: That does not correspond to the scene, activity, or context.

Restrictions: Relationships between the concepts that allow obtaining basic characteristics of the scene.

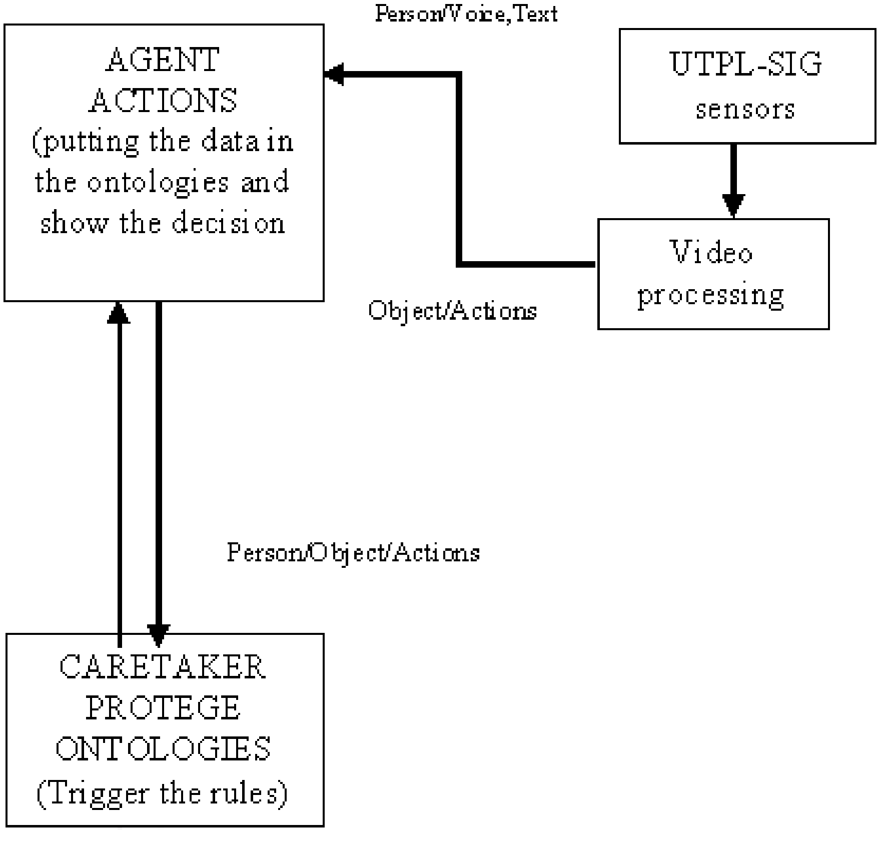

Figure 3. The sensors detecting an object or person, after the ontology using this information to determinate the actions and answer with the rules.

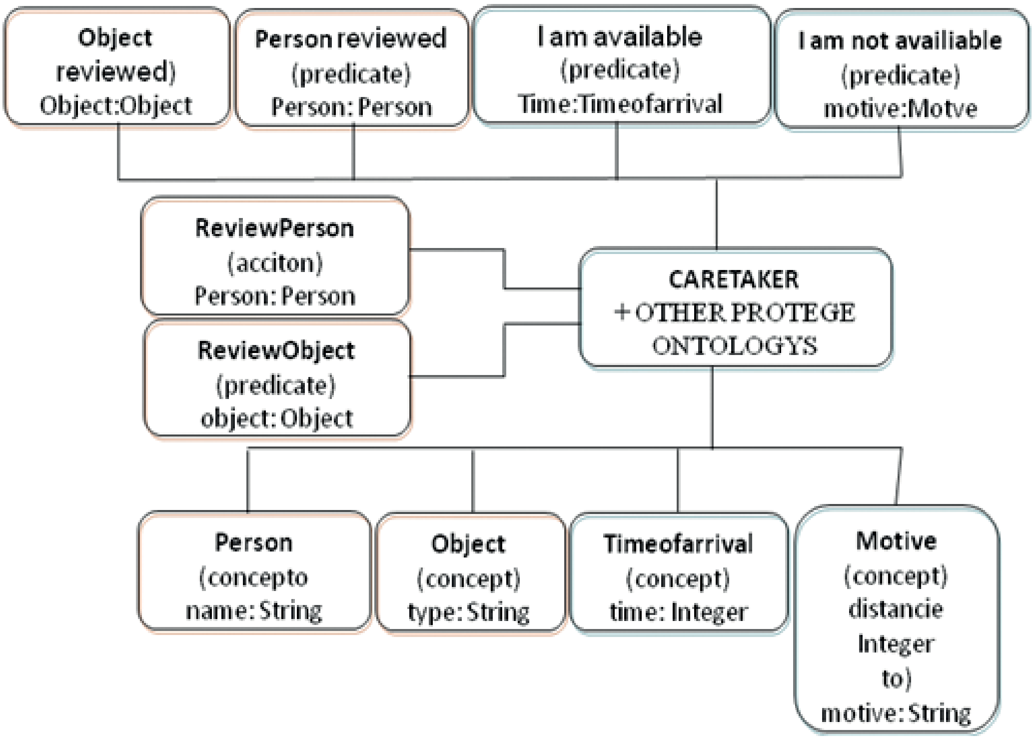

Figure 4. Our CARETAKER ONTOLOGY.

Description of a model and an associated instance, respectively, of a primitive state, a primitive event, and an event composed of multiple agents (see (CAREGIVER)). The code to conceptualization:

```
package surveillanceontology;
import jade.content.Concept;
public class Persona implements Concept {
  private String nombres;
  public String getNombres() {
    return nombres;
  }
  public void setNombres(String n) {
    nombres = n;
  }
}
```

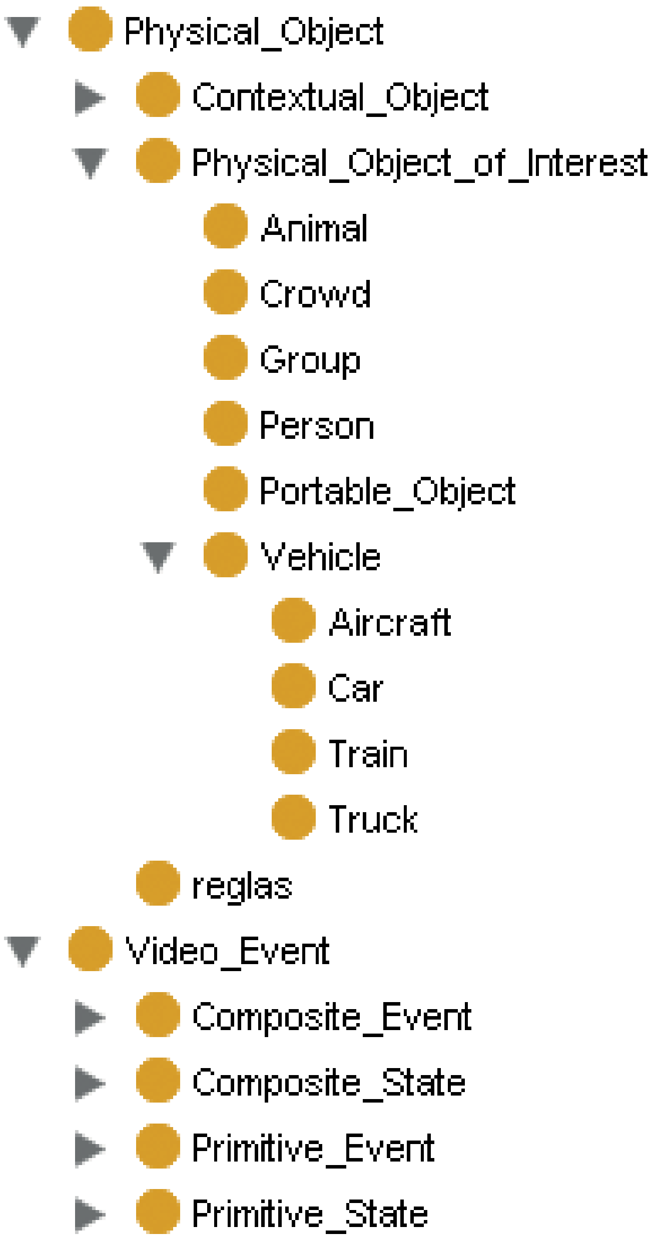

Figure 5. CARETAKER ONTOLOGY.

PrimitiveState_Inside_zone

PhysicalObjects_

(p: Person, z: Zone)

Constraints:

(p in z)

Instance:

S1: **PrimitiveState_Inside_zone_**(Hector, ZonaProhibida)

CompositeEvent SigOfficeEntrance

PhysicalObjects:

(e : Persona[worker], r: Persona**[Hector]**

Components:

((c1: PrimitiveState Inside_zone (e, "Back_Counter"))

(c2: PrimitiveEvent Changes_zone(r, "Entrance_Zone", "Front_Count")

(c3: PrimitiveState Inside_zone (e,"Safe"))

(c4: PrimitiveState Inside_zone(r,"Safe")))

Constraints:

((duration-of(c3) >= 1 second)

(c2 during c1)

(c2 before c3)

(c1 before c3)

(c2 before c4)

(c4 during c3))

Instance:

e2: CompositeEvent SigOfficeEntrance

Ontology has two uses: (a) semantics for the occurrence of events, through states and events with little granularity in which the occurrence of physical events is highlighted. Here, we describe the attributes of each thing and the relationships between them, in order to obtain a clear description of the scene under study. The levels of implementation allow the use of the restrictions based on time and space, which means that the states and events that occur in the video can have their location and semantic description. This basic corpus can be refined depending on the needs. Refined concepts are more difficult to extract from videos. For example, they may need posture analysis algorithms. The concept "holding an object" is perceived differently depending on the posture but also in the properties of the held object. Holding a gun is perceptually different from holding a luggage.

The proposed corpus should be seen as an extendable basis. The issue is now to define tools and protocols to allow a collaborative extension of the corpus.

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4. Alarm-agent-caretaker

This job uses the Protégé software for using the CARETAKER ontologies and it configurates the ontology for our benefit. At the time, it is necessary to transform the classes in the CARETAKER ONTOLOGY in java classes using the BeanGenerator plugging for this process. This is important because the agents use the ontology in java code when the alarm generates the agent. Using this generation puts the data in the java CARETAKER ONTOLOGY, and this ontology returns as the decisions for the agent. For this reason, communication takes place in two ways: the first time from sensor-agent-ontology and the second after ontology agent.

5. The style

When the sensor catches a person/object/action, the system uses this steps to determinate if it is a person, object, or action. After these, data is sending at the CARETAKER ONTOLOGY for taking decisions. The equation for the image binary is:

$$\begin{gathered} \mathrm{img}(i,j) = \begin{cases} \mathrm{imgG}(i,j) > \text{umbral entonces } \mathrm{img}(i,j) = 1 \\ \\ \mathrm{imgG}(i,j) < \text{umbral entonces } \mathrm{img}(i,j) = 0 \end{cases} \\ \mathrm{imgN}(i,j) = 1 - \mathrm{img}(i,j) \end{gathered} \tag{1}$$

On the other side, detecting movement is necessary to establish the difference between the bottom image (principal image) and the image caught by sensors. Using this equation for knowing the difference

$$suma = \sum_m \sum_n (resta_{mn}) \tag{2}$$

This methodology was used in this job to recognize these activities:

1. Person in the office
2. Persons in the office
3. Objects in the desk

In this moment the system determinates if the person is in the office and if an object was subtracted from the office or another action in the scene. Good, the system has the words person and object in a file with the name saved; for example, in **Figure 3** the system recognizes the people, and this image is labeling with the word person recognition. The process is the same for object and actions.

Well, when the systems recognize a person in the class (CARETAKER ONTOLOGY), it is an instance because it is necessary to identify if the person has the permission for this site or not. In this moment the alarm is generated: the system recognizes a person and the rule. If the person is in the office when the time is higher at 21:h00, then it calls the security in charge to review the person in the place. Security is subclass from person class.

The action reviews if the person is in the ontology due to the connection between person recognition and the decisions after the alarm. At the same time, when the security person reviews at people recognized in the site, the message will come back before reviewing the person.

A difficult remaining problem is the segmentation process. Indeed, in order to be classified, images have to be segmented to allow descriptor computation. The symbolic description made by the expert may help finding the image processing tasks required for extracting the pertinent information from the provided images.

As an example, an object described with the "granulated texture" concept may be segmented with a texture-based segmentation algorithm. The regions of interest selected by the expert (see 1) in this work use the img (i, j) to correct this problem.

The system uses the natural language for decisions: the agents are programmed using JADE (Java Agent Development Framework) and the natural language coded to communicate the agents:

Jade enterprise

Alarmado (generating the alarm)

Security central (receive the alarm and using the ontology for making a decisions)

On the other side, the system uses the file saved to communicate the sensors with the alarm agent. This is important because the alarm has code lines to review each 10 seconds if the file.txt has the word: person recognition, object recognition, or actions after producing the after process.

Author details

Lozada Torres Edwin Fabricio[1], Martínez Campaña Carlos Eduardo[1] and
Gómez Alvarado Héctor Fernando[2]*

*Address all correspondence to: hf.gomez@uta.edu.ec

1 Universidad Regional Autónoma de los Andes, Ambato, Ecuador

2 Universidad Técnica de Ambato, Huachi Chico, Ambato, Ecuador

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Spiking Central Pattern Generators through Reverse Engineering of Locomotion Patterns

Andrés Espinal, Marco Sotelo-Figueroa,
Héctor J. Estrada-García,
Manuel Ornelas-Rodríguez and
Horacio Rostro-Gonzalez

Additional information is available at the end of the chapter

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Abstract

In robotics, there have been proposed methods for locomotion of nonwheeled robots based on artificial neural networks; those built with plausible neurons are called spiking central pattern generators (SCPGs). In this chapter, we present a generalization of reported deterministic and stochastic reverse engineering methods for automatically designing SCPG for legged robots locomotion systems; such methods create a spiking neural network capable of endogenously and periodically replicating one or several rhythmic signal sets, when a spiking neuron model and one or more locomotion gaits are given as inputs. Designed SCPGs have been implemented in different robotic controllers for a variety of robotic platforms. Finally, some aspects to improve and/or complement these SCPG-based locomotion systems are pointed out.

Keywords: central pattern generators, spiking neural networks, reverse engineering, metaheuristic, locomotion patterns

1. Introduction

Since its beginning, robotics has been a research field strongly influenced by nature. For robotic platforms where wheels to displace themselves are not used, researchers have taken inspiration not only in the physical form of living beings as archetypes of their designs (e.g., legged, finned or winged robotic platforms), but also in the mechanisms to allow their locomotion (e.g., walking, swimming or flying), mainly known as central pattern generators (CPGs) [1]. In biology, the basis of CPGs was settled down in Brown's studies about how the rhythmic movements of locomotion in living beings are created [2]. In [3], Brown experimentally discovered that neurons, which inhibiting each other, generate periodically rhythmic activities that control bending and tension of muscles involved in locomotion. Moreover, GPGs have been linked to other unconscious activities besides locomotion such as swallowing, digestion, heart beating and breathing [4, 5].

Furthermore, CPGs have become a suitable alternative to nonbiologically inspired methods for locomotion systems of nonwheeled robotic platforms [6]; this is due to several and interesting features of CPGs such as adaptability, rhythmicity, stability and variety [7]. The CPG-based locomotion systems have been successfully designed and implemented at software and/or hardware levels for different nonwheeled robotic platforms [8] such as walking robots (biped [9], quadruped [10], hexapod [11] and octopod [12]), swimming robots [13], flying robots [14]), among others (i.e., snake robots [15] and salamander robots [16]). Although vast amount of works made and reported in the state of the art about CPG-based locomotion systems, there is not a general and standard methodology to build CPGs [6]; however, working with CPGs commonly involves the following three phases [7]: (1) choosing the processing unit model, the coupling type and the connectivity topology (modeling and analysis), (2) dealing with parameter tuning, usually solved by optimization methods and gait transition, to handle variation on gaits as type or frequency (modulation) and (3) executing the designed CPG at the software and/or hardware level (implementation).

In this chapter, we focus on locomotion systems for legged robots, which are based on spiking central pattern generators (SCPGs) and reverse engineering methods for automatically design them. The study and implementation of SCPGs as locomotion systems have been barely explored and compared with other CPGs, which are built with oscillators or low-plausible neuron models (see [6, 7, 17] as reference). The SCPGs are built with plausible neuron models known as spiking neurons, models that define the third generation of artificial neural networks [18]; these neuron models naturally receive and send spatio-temporal information as generating rhythmic patterns are required for CPGs. The SCPGs have been designed and implemented as locomotion systems for robotic platforms such as bipeds [19–21, 25], quadrupeds [23, 25] and hexapods [22, 24–27], where the design methodologies used in [19–21, 27] tend to follow the phases proposed in [7], while in [22–26] reverse engineering methods are used. Basically, a reverse engineering method to design SCPG-based locomotion systems for robotic platforms uses either deterministic or stochastic optimization methods, which, given an input set of discretized rhythmic signals and a fixed spiking neuron model, are capable of defining a spiking neural network (SNN), including both synaptic connections and weights, that endogenously and periodically replicates the input set of discretized rhythmic signals, which contribute to locomotion of a robotic platform. Herein, we present a generalization of reverse engineering methods to design SCPG-based locomotion systems for robotic platforms based on details of implementations of reviewed works.

2. Robotic platforms and controllers

Nowadays, there are a variety of robotic platforms, and each of them has particular technical specifications in design, displacement ways and so on. In reviewed works, for real implementations of SCPG-based locomotion systems, three types of legged robotic platforms have been particularly used such as hexapod, quadruped and biped robots. Particularly, the used robotic platforms have 3 degrees of freedom (DOFs) or servomotors per leg, that is, the hexapod has 18 DOFs, the quadruped has 12 DOFs and the biped has 6 DOFs. Although for the hexapod and the quadruped, just two DOFs per leg were used; the two are closer to the body of robots and directly related to the movement of the robot. **Figure 1** shows the robotic platforms with a specific label for identifying the position of their respective servomotors.

Servomotors in the robotic platforms are handled by a processing unit, which in reviewed works, a SCPG is embedded into them to provide a locomotion mechanism to the robots. In **Figure 2**, we present the electronic boards, which have been used as processing units such as

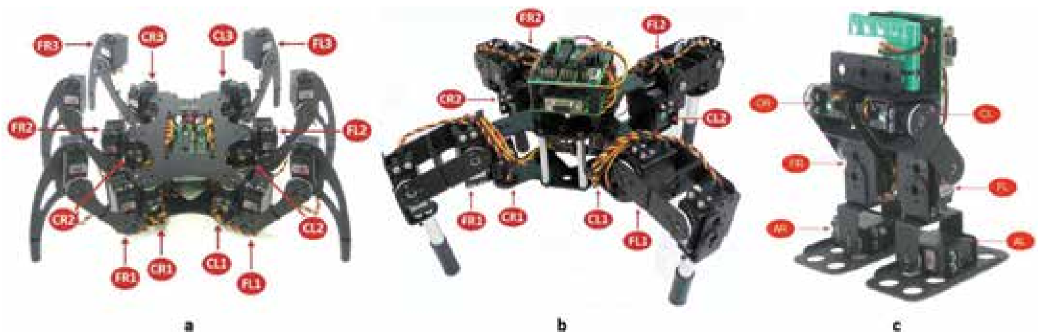

Figure 1. Robotic platforms from Lynxmotion company. (a) Phoenix hexapod robot model, (b) symmetric quadruped robot model and (c) Brat biped robot model. In ovals are marked and labeled the servomotors used in their locomotion where letters C, F and a stand for Coxa, femur and ankle, respectively, letters L and R represent left and right sides, and numbers mark the number according to their position (taken from [25]).

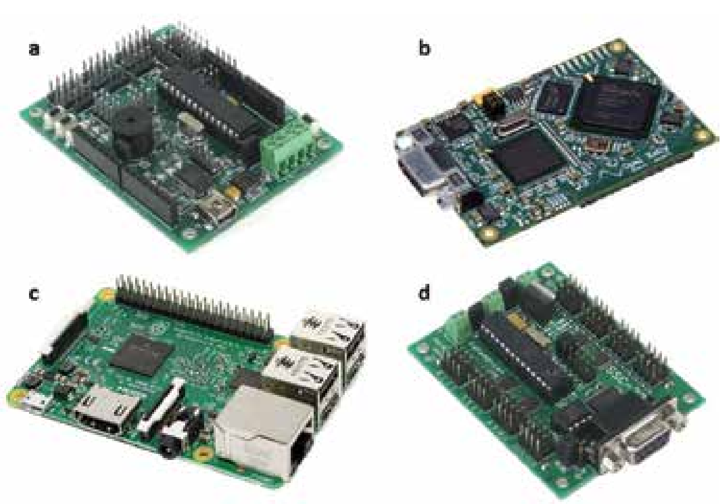

Figure 2. Boards for robot control. Processing units: (a) Arduino board, BotBoarduino for Lynxmotion robots, (b) FPGA Spartan 6 XEM6310-LX45 board from OpalKelly, and (c) Raspberry Pi 3 Model B board. Servo controller: (d) SSC-32 board.

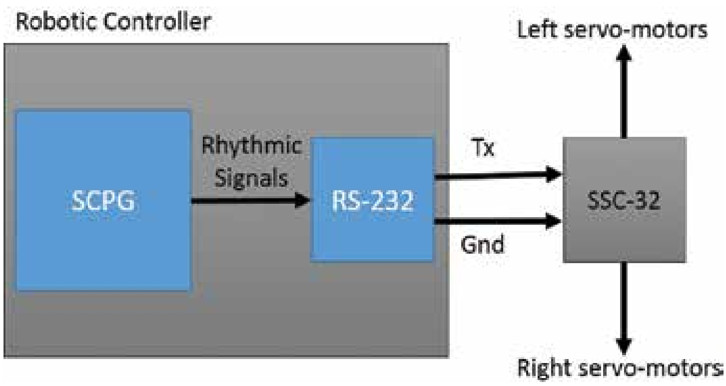

Figure 3. System block diagram of robotic controller coupled with servomotors of robotic platforms through a servo controller.

Arduino (**Figure 2a**), Field Programmable Gate Array (FPGA) (**Figure 2b**) and a Raspberry Pi 3 Model B (**Figure 2c**) boards. Also, a servo controller board (**Figure 2d**) is required to send the output of the processing units to the servomotors of the robotic platforms.

Basically, the integration of the processing boards and platforms works as follows: an embedded SCPG into a processing board generates rhythmic signals, which are sent to the legs through a servo controller. This converts the spiking activity generated by the SCPGs into a control signal (voltage). The transmission process is carried out by using the RS-232 communication protocol. **Figure 3** shows a block diagram of this integration.

Thus, an important aspect to achieve locomotion in robotic platforms is to design a SCPG according to the capabilities of the processing board, which, for reviewed works, must exactly replicate and periodically generate specific rhythmic patterns. In Section 3, we describe in detail the functionality of SCPGs and methods used for designing them.

3. SCPG-based locomotion system

The SCPGs, reviewed in this chapter, can generate endogenously discrete rhythmic signals; in other words, each periodical signal of a locomotion gait is represented by means of a spike train with spike times occurring periodically. This idea was firstly presented by Rostro-Gonzalez et al. in [22], where SCPGs built with discrete spiking neurons (Section 3.2.1) were automatically designed by using a deterministic reverse engineering method (Section 4.1) to imitate walking forms of a stick insect; based on steps sketches of walking forms of stick insect reported in [28], Rostro proposed three sets of discrete rhythmic signals as locomotion gaits (Section 3.1) to achieve hexapod robot locomotion by means of designing one SCPG for each of them.

In **Figure 4**, Rostro-Gonzalez's approach to achieve locomotion for six-legged robots through discrete events over time by means of SNNs is schematized. In **Figure 4a**, a walking form of stick insect reported in [28] is presented; black rectangles represent a leg on ground, while white ones represent a leg in the air. The L1 row is marked with dotted rectangle to exemplify

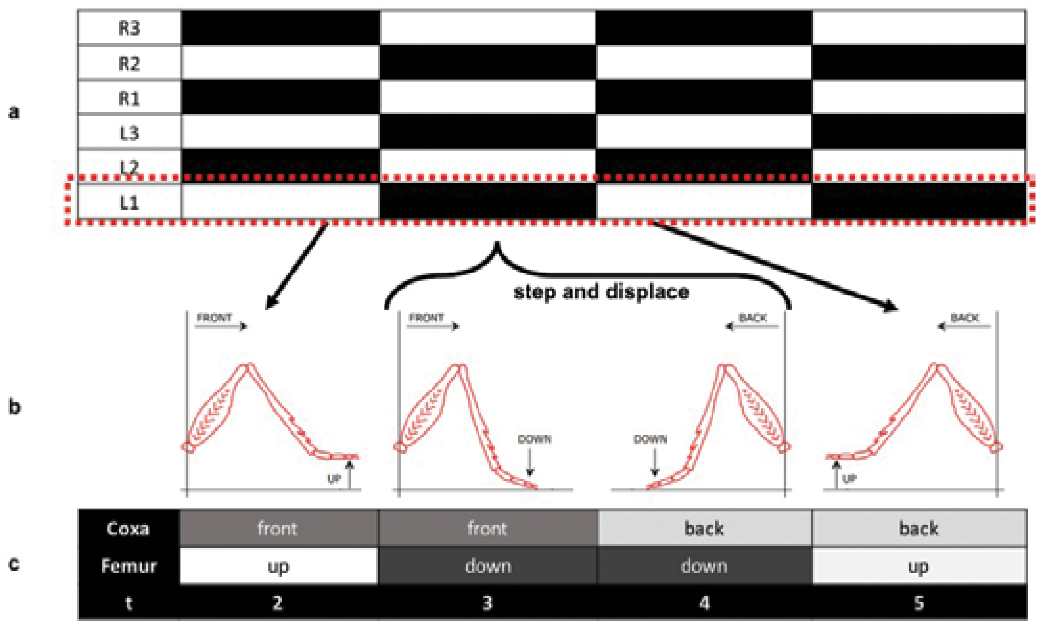

Figure 4. Representation of extrapolation of steps observed of hexapod insect into discrete rhythmic signals for SCPG-based locomotion design. (a) Walking form of stick insect reported in [28], (b) extrapolation of a step into position of a leg over time and (c) proposal of a step (femur row) with additional information (coxa row) represented as spike trains, in each row, darker rectangles represent a spike and lighter ones indicate the absence of spike.

how a step of real hexapod insect is interpreted and extended to a step of robot hexapod. Notice in **Figure 4b** that leg sketch coincides with a black rectangle in **Figure 4a** as leg is on the ground, and at this point the leg displacement that contributes to whole walking action occurs. **Figure 4c** shows the rhythmic signals over time to move a leg according to locomotion gait in **Figure 4a**; the coxa moves to front with spike events and to back without spike events, while the femur moves to down with spike events and to up in the absence of spike events. Finally, the combination of such movements according to the presence and absence of spikes of all legs provokes locomotion of legged robot.

Later, Espinal et al. generated SCPG-based locomotion systems for quadruped and hexapod robots based on Rostro-Gonzalez's idea by using the same discrete spiking neuron model (Section 3.2.1) and a stochastic reverse engineering (Section 4.2) for designing them. There were designed and implemented SCPG-based locomotion systems for quadruped robots in [23] and hexapod robots in [24]; the difference with the Rostro's work is that more compact SNN topologies were achieved, and it was achieved to design a single SCPG capable of generating the three original locomotion gaits for hexapod robots and was extended for quadruped ones as well.

Lately, SCPG-based locomotion systems for hexapods, quadrupeds and bipeds were designed by Guerra-Hernandez et al. in [25]. In his work, there was proposed a locomotion gait for biped robots following the Rostro's idea, and SNNs were designed by using the discrete spiking neuron model and a variant of stochastic reverse engineering (Section 4.2) proposed by Espinal et al.

Lately, in [26], Perez-Trujillo et al. designed SCPG-based locomotion systems for hexapod robots based on Rostro-Gonzalez's, Espinal's and Guerra-Hernandez's works. The contribution of Perez-Trujillo's work was to create SCPG-based locomotion systems built with a nondiscrete spiking neuron model (Section 3.2.2), and the reverse engineering method was a variant stochastic one (Section 4.2).

The reviewed works are summarized in **Table 1**, including robotic platforms and processing boards as well as reverse engineering method and spiking neuron model used.

Following subsections complement the description of SCPG-based locomotion systems. In Section 3.1, the different rhythmic signal sets reported for each locomotion gait to robotic platforms are shown. Section 3.2 describes the spiking neuron models that have been used to define SNN as SCPGs on robot locomotion.

3.1. Locomotion patterns

The locomotion patterns contain the discrete rhythmic signals for each servomotor of a robotic platform. Each of them serves to define a specific locomotion gait that a SCPG must replicate endogenously and periodically. Besides, they are used for engineering reverse methods (Section 4) to design SCPGs. In **Figures 5–7**, show the different designed discrete rhythmic signals for hexapod, quadruped and biped robots, respectively; for each row corresponds a servomotor with the same label according to the robotic platform.

3.2. Spiking neuron models

3.2.1. Beslon-Mazet-Soula neuron model

The Belson-Mazet-Soula (BMS) neuron [29] is a discrete-time model derived from a well-known spiking neuron, that is, the integrate-and-fire [30] model. The BMS neuron model is defined by Eqs. (1) and (2), and they describe the behavior of the *i*-th neuron over time *k*; former equation models its membrane potential V_i, and the last equation defines its firing state Z_i.

Author/Work	Robotic platform	Robotic controller	Spiking neuron model	Reverse engineering method
Rostro et al. [22]	Hexapod	FPGA	BMS Neuron	Deterministic
Espinal et al. [23]	Quadruped	Arduino	BMS Neuron	Stochastic
	Hexapod	FPGA		
Espinal et al. [24]	Hexapod	FPGA	BMS Neuron	Stochastic
Guerra et al. [25]	Hexapod	FPGA	BMS Neuron	Variant stochastic
	Quadruped	FPGA		
	Biped	FPGA		
Perez et al. [26]	Hexapod	Raspberry Pi 3	LIF Neuron	Variant stochastic

Table 1. Summary of Legged Robot Locomotion System Configurations and reverse engineering methods.

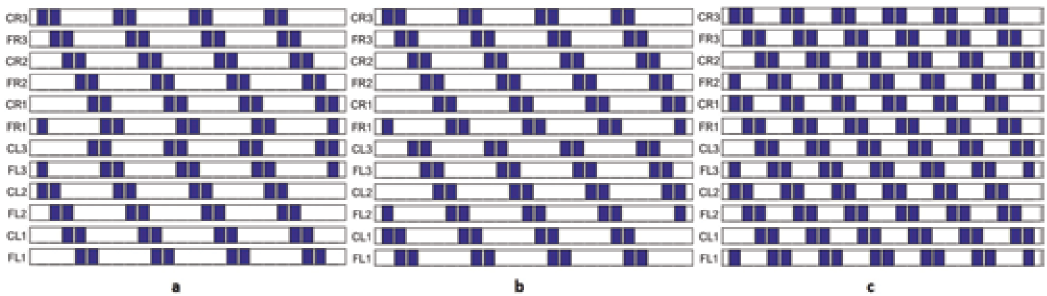

Figure 5. Hexapod robot locomotion gaits proposed in [22] (figures taken from [26]). (a) Walk gait, (b) jog gait and (c) run gait.

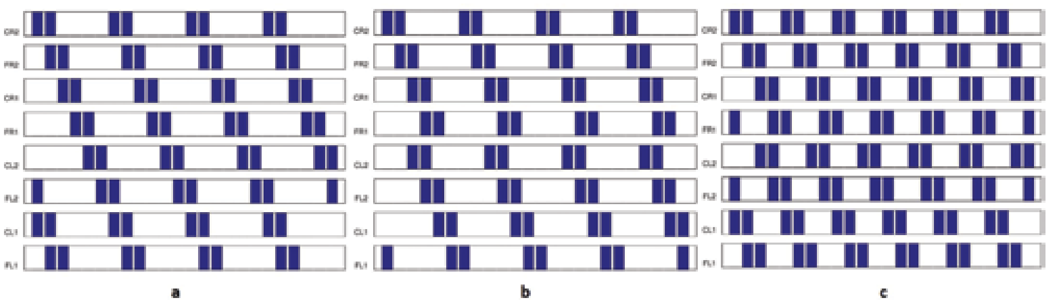

Figure 6. Quadruped robot locomotion gaits proposed in [23] (figures taken from [26]). (a) Walk gait, (b) jog gait and (c) run gait.

Figure 7. Biped walking locomotion gait proposed in [26].

$$V_i[k] = \gamma V_i[k-1](1 - Z_i[k-1]) + \sum_{j=1}^{N} W_{ij} Z_j[k-1] + I_i^{ext} \tag{1}$$

In Eq. (1), $\gamma \in [0, 1]$ represents the leaky factor. The number of spiking neurons into the neural network is given by N. The synaptic strength weights are given by W_{ij}. The I_i^{ext} is either a varying or constant external stimuli; due to that, CPGs endogenously produce periodic patterns $I_i^{ext} = 0$.

$$Z_i[k] = \begin{cases} 1 & \text{if } V_i[k] \geq \theta \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

For Eq. (2), the fixed firing threshold is given by θ. Eq. (2) is used in Eq. (1) for tracking spike occurrence ($Z_i[k]$) and resetting the membrane potential of i-th neuron $(1 - Z_i[k])$.

3.2.2. Integrate-and-fire neuron model

The integrate-and-fire (I&F) neuron [30], basically, models the evolution of its membrane potential's state over time as a resistor-capacitor (RC) circuit. In particular, the current-based leaky integrate-and-fire (LIF) model, or "if_curr_exp" model in the PyNN library [31], is a LIF neuron with a fixed firing threshold and exponentially decaying postsynaptic conductance given in Eq. (3); besides, the model requires of *tau_refrac* to define the refractory value and *v_thresh* to set the fixed firing threshold.

$$\frac{dv}{dt} = \frac{ie + ii + i\_offset + i\_inj}{c\_m} + \frac{v\_rest - v}{tau\_m} \tag{3}$$

In Eq. (3), the membrane potential is represented with v. The excitatory and inhibitory current injections *ie* and *ii* are modelled by differential equations in Eqs. (4) and (5), respectively. The *i_offset* stands for a base input current, and *i_inj* is an external current injection; both added each timestep, but $i\_inj = 0$ due to the nature of CPGs.

$$\frac{die}{dt} = -\frac{ie}{tau\_syn\_E} \tag{4}$$

$$\frac{dii}{dt} = -\frac{ii}{tau\_syn\_I} \tag{5}$$

Finally, tau_syn_E and tau_syn_I, in Eqs. (5) and (6), are excitatory and inhibitory input current decay time constant.

4. Reverse engineering methods for designing SCPGs

In this section, we describe reverse engineering methods for automatically design SNNs by defining both their topology and synaptic weights. The reviewed methods can be generalized in diagram shown in **Figure 8**.

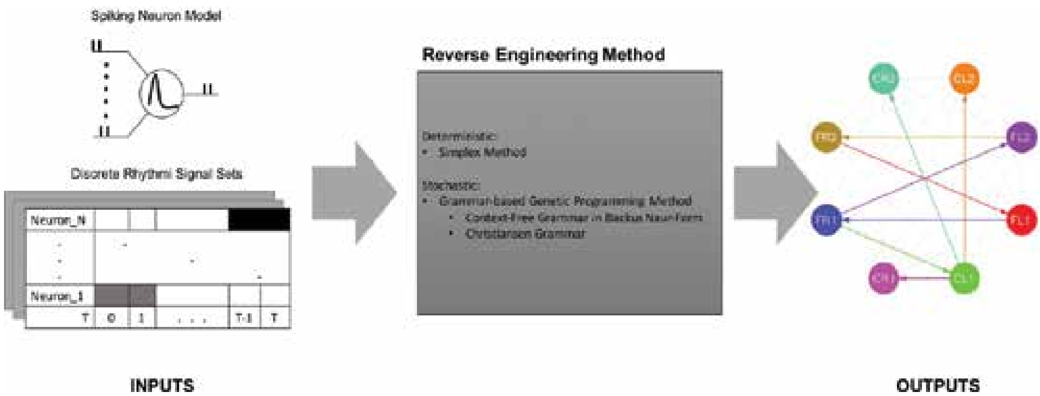

Figure 8. Diagram of reverse engineering method for designing SCPG.

Basically, the generalization defines an input-process-output system where its inputs are a fixed spiking neuron model (Section 3.2) and one or more sets of discrete rhythmic signals (Section 3.1), and the process is defined according to an optimization method, which can be deterministic (Section 4.1) or stochastic (Section 4.2). Finally, the output is generally a partially connected, directed and weighted graph that defines all aspects of a SNN to behave as a SCPG.

Next, the optimization is briefly described, and their strengths and weaknesses are pointed out.

4.1. Deterministic method: Simplex method

This method, originally proposed by Rostro in [34], was created to build SNNs to replicate recorded biological neural dynamics. It was developed to work with the BMS spiking neuron model (Section 3.2.1). It is described in [22] as follows:

First, Eq. (1) must be rewritten in form expressed in Eq. (6).

$$V_i[k] = \sum_{j=1}^{N} W_{ij} \sum_{\tau=0}^{\tau_{ik}} \gamma^{\tau} Z_j[k-\tau-1] + I_{ik\tau} \tag{6}$$

where $I_{ik\tau} = \sum_{\tau=0}^{\tau_{ik}} \gamma^{\tau} I_i^{(\mathrm{ext})}[k-\tau]$ with: $\tau_{ik} = k-$ arg $\min_{l>0}\{Z_i[l-1]=1\}$; see [34] for derivation details. With Eqs. (1) and (2), a linear programming system can be formulated to determine the synaptic connections and weights of SNNs, which replicates locomotion gaits represented as rhythmic spiking dynamics through the evolution of all $V_i[k]$ (the membrane potential of each spiking neuron into the network), which are not known. Now, we define the expression: $Z_i[k] = 0 \Leftrightarrow V_i[k] < \theta$ and $Z_i[k] = 1 \Leftrightarrow V_i[k] \geq \theta$; where $\theta = 1$ for simplification. Last expression can be written as next inequality: $Z_i[k] = 0 \Leftrightarrow V_i[k] < \theta$.

By substituting Eq. (6) in the last expression, we can get a linear programming system [35], given the expression in Eq. (7).

$$e_i = A_i w_i + b_i \geq 0 \tag{7}$$

where

- $A_i = \begin{pmatrix} \cdots & \cdots & \cdots \\ \cdots & (2Z_i[k]-1)\sum_{\tau=0}^{\tau_{ik}} \gamma^{\tau} Z_j[k-\tau-1] & \cdots \\ \cdots & \cdots & \cdots \end{pmatrix}$
- $b_i = (\cdots \ (2Z_i[k]-1)(I_{ik\tau}-1) \ \cdots)^t$
- $w_i = \begin{pmatrix} \cdots & W_{ij} & \cdots \end{pmatrix}^t$
- $e_i = (\cdots \quad (2Z_i[k]-1)(V_i[k]-1) \quad \cdots)^t$

Solving the aforementioned formulated linear programming problem in Eq. (7), by using a simple method (or any existing linear programming solver), we obtain the synaptic weights of all neurons and, indirectly, a SNN topology.

Next, the features of this method are listed as follows:

- Strengths:
    - The definition of whole SNN is made by executing the method once.
    - It has been successfully used as a reverse engineering method for designing SNNs, which replicate recorded biological neural dynamics.
- Weaknesses:
    - It can design SNN by using only BMS spiking neuron models.
    - It generates one SNN for replicating just one neural dynamic pattern.

4.2. Stochastic method: Grammar-based genetic programming

For stochastic reverse engineering methods, evolutionary algorithms have been used; particularly, a variant of well-known genetic programming [36] called grammatical evolution (GE) [37]. Practically, GE is an optimization tool that searches approximated optimal solutions by representing them indirectly for a given problem; thus, working with GE to solve a specific problem requires four components: problem instance(s), representation of solutions, a fitness function to evaluate solution's quality and a search engine.

For the SCPG design problem, two types of representations have been proposed: one as a Context-Free Grammar (CFG) in Backus-Naur Form (BNF) and another as a Christiansen Grammar (CG) to use GE (in [25, 26]) and a variant called Christiansen Grammar Evolution (CGE) [38] (in [23, 24]), respectively. In general, both representations describe languages that define the presynaptic connectivity (including weights) of a specific spiking neuron; the common structure of expected words of two grammars is as follows: $\overbrace{id_1, weight_1}^{1st\ configured\ synapse} |\cdots| \overbrace{id_n, weight_n}^{n-th\ configured\ synapse}$. The connectivity defined by a word has at least one connection and a maximum of connections according to number of neurons into the SNNs. The main difference between both representations is that words of CG representation are syntactically and semantically correct, this means that any generated word is valid and there are not repeated indexes, while words of CFG BNF are just syntactically correct or any generated word is just valid.

The fitness function is usually defined by the problem; to solve this, three fitness functions based on SPIKE [39] (used in [23, 24, 26]) and Victor-Purpura distances [40] (used in [25]) to compare similarity between generated spike train and target spike train to guide the search process have been proposed. Basically, first and second distance-based fitness functions are for generating one SCPG per locomotion gait; the difference is that the second one looks for minimal presynaptic connectivity and the first one does not care about number of presynaptic connections. The third distance-based fitness function allows to generate a single SCPG, which can replicate different locomotion gaits.

The search engine in GE is usually a metaheuristic algorithm, which tries to improve the quality of solutions. For reviewed works, three different algorithms have been used: Univariate Marginal Distribution Algorithm [40] (used in 23), (1 + 1)-Evolution Strategy [41] (used in [24]) and Differential Evolution [42] (used in [25, 26]).

For implementation details, see [23–25]. Next, the features of this method are listed:

- Strengths:
    - It can design SNNs which use either BMS spiking neuron model or LIF neuron model.
    - It can handle design criteria to design compact SNN topologies or SNN, which can replicate different neural dynamics or locomotion gaits.
- Weaknesses:
    - The process must be executed several times to build a single SNN; due to that, it defines synaptic connection and weights one neuron at time.
    - It has not been tested on other design problems than design SCPGs.

5. Discussion and conclusion

Nowadays, autonomous robot locomotion is still a valid problem that has been partially solved in robotics. Particularly, locomotion of nonwheeled robotic platforms is a problem highly susceptible for trying to be solved by means of bioinspired algorithms known as CPGs. However, sometimes working with CPGs may represent a problem itself since its design; this is due to the different choices that must be made before implement the CPG according to [7]. In this chapter, we have explored researches made on SCPG field, a particular type of CPGs, which have been barely explored to date. The SCPGs are built with spiking neurons, a plausible neuron model, which handle similar information as such observed in biological neural systems. We specifically focus on SCPG designed by approaches that allow to dispense with human experts for explicitly define each CPG design phase. These kinds of works use reverse engineering methods to solve de SCPG design problem as an optimization one. By means of these methods, there are generated weighted and directed graphs as SNNs, which endogenously generate rhythmic discrete signals to allow locomotion of legged robots.

Biological CPGs do not work in isolation; they depend on the information interaction with other parts of the central nervous system [32]; even, external afferent inputs are used to shape their outputs [33]. Based on the aforementioned, the next step of SCPG-based locomotion systems could be their integration in navigation systems to endow them with sensors and can build more robust and plausible bioinspired algorithms.

Finally, there are other reasons to keep studying and implementing SCPGs, which go far beyond the locomotion of nonwheeled robots, their possible application in other areas, like medicine in developing prosthetic robotic devices for patients with spinal damage or amputated limbs [20].

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Author details

Andrés Espinal[1*], Marco Sotelo-Figueroa[1], Héctor J. Estrada-García[2], Manuel Ornelas-Rodríguez[3] and Horacio Rostro-Gonzalez[4,5]

*Address all correspondence to: aespinal@ugto.mx

1 Department of Organizational Studies, DCEA-University of Guanajuato, Guanajuato, Mexico

2 Department of Electrical Engineering, DICIS-University of Guanajuato, Salamanca, Mexico

3 Division of Postgraduate Studies and Research, ITL-National Technology of Mexico, Leon, Mexico

4 Department of Electronic Engineering, DICIS-University of Guanajuato, Salamanca, Mexico

5 Neuroscientific System Theory, Department of Electrical and Computer Engineering, Technical University of Munich, Munich, Germany

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Chapter 5

Characterizing Motor System to Improve Training Protocols Used in Brain-Machine Interfaces Based on Motor Imagery

Luz Maria Alonso-Valerdi and
Andrés Antonio González-Garrido

Additional information is available at the end of the chapter

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Abstract

Motor imagery (MI)-based brain-machine interface (BMI) is a technology under development that actively modifies users' perception and cognition through mental tasks, so as to decode their intentions from their neural oscillations, and thereby bringing some kind of activation. So far, MI as control task in BMIs has been seen as a skill that must be acquired, but neither user conditions nor controlled learning conditions have been taken into account. As motor system is a complex mechanism trained along lifetime, and MI-based BMI attempts to decode motor intentions from neural oscillations in order to put a device into action, motor mechanisms should be considered when prototyping BMI systems. It is hypothesized that the best way to acquire MI skills is following the same rules humans obey to move around the world. On this basis, new training paradigms consisting of ecological environments, identification of control tasks according to the ecological environment, transparent mapping, and multisensory feedback are proposed in this chapter. These new MI training paradigms take advantages of previous knowledge of users and facilitate the generation of mental image due to the automatic development of sensory predictions and motor behavior patterns in the brain. Furthermore, the effectuation of MI as an actual movement would make users feel that their mental images are being executed, and the resulting sensory feedback may allow forward model readjusting the imaginary movement in course.

Keywords: motor system, forward model, inverse model, brain-machine interfaces, training protocols

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1. Introduction

Electroencephalography (EEG) has become a standard brain imaging tool due to its viability for recording the brain activity. Typically, EEG has been analyzed by quantifying and qualifying neural oscillations. In broad terms, "neural oscillations" can be defined as spatial, temporal, and spectral patterns that are associated with particular perceptual, cognitive, motor, and emotional processes [1]. A large and growing body of literature has investigated neural oscillations as EEG feature in all directions: from neurological to technological perspectives. In terms of Neurosciences, research into brain response has a long history. Brain responses have been traditionally studied on the basis of event-related experiments, where time-locked and phase-locked responses (i.e., event-related potentials) along with time-locked but not necessary phase-locked responses (i.e., event-related (de) synchronization) have been essentially analyzed [2, 3]. In the case of technology, research into neural interfaces has taken a leading role. A neural interface is a system that permits to reintegrate the sensory-motor loop, accessing directly to brain information. There are three main types of neural interfaces: (1) sensory interfaces, which artificially activate the sensory system; (2) cognitive interfaces, which try to re-establish the communication of the neural networks; and (3) motor interfaces, which translate neural oscillations into control commands for a device of interest [4]. In particular, motor interfaces are known as brain-machine interfaces (BMI).

BMIs are technology under development that modify users' perception and cognition in order to decode their intentions from their neural oscillations, and thereby bringing some kind of activation. See **Figure 1**. Human perception and cognition can be manipulated actively through

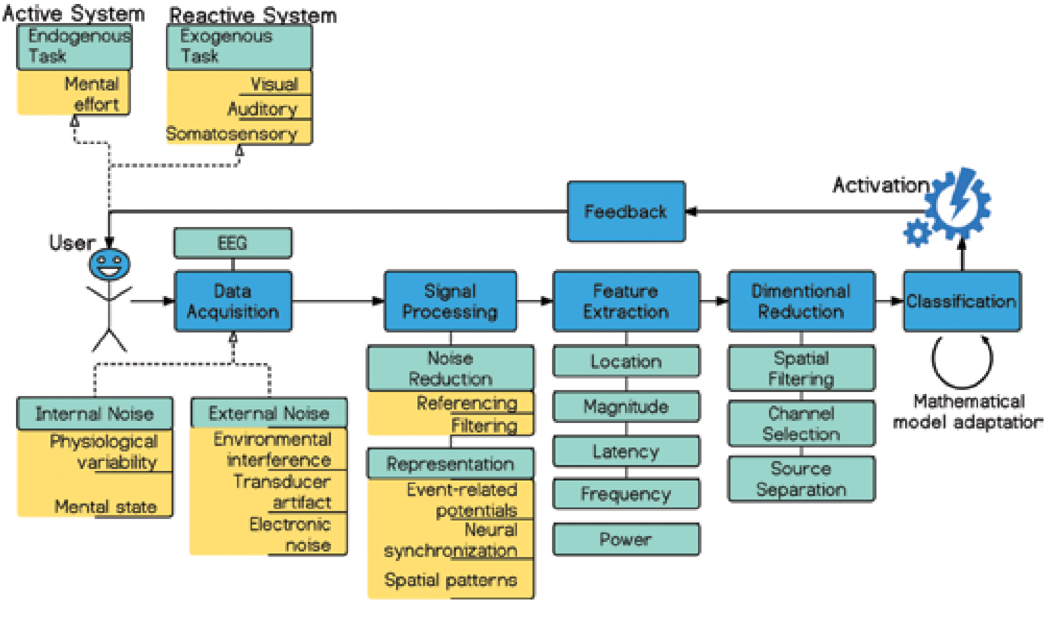

Figure 1. Structure of a brain-machine interface (BMI). The basic structure of a BMI is based on user, control task (endogenous or exogenous), data acquisition, signal processing, feature extraction, dimensional reduction, classification, activation (e.g., neuro-feedback, neuro-prosthesis, domotic environments), and feedback.

mental tasks, or reactively by applying external stimulation (visual, auditory, or somatosensory). Users' intentions are typically decoded by reducing EEG signal noise, extracting neurophysiological features associated with the mental task or the external stimulus in use, and adapting a mathematical model by using those features [5]. Once a model has been calibrated, the BMI attempts to predict users' intentions so as to bring activation in different ways, including neuro-rehabilitation, communication, neuro-prosthesis, domotic environments, or neuro-feedback [6]. In a nutshell, BMI has been the operationalization of Neuroscience research advances.

Although BMI investigation was firstly undertaken in the 60s, these systems are still laboratory prototypes because (1) it is unknown how EEG features are linked to perception and cognition (human side); (2) users have been not involved in the system design, are usually not well instructed, and not guided during the user-system adaption (human-machine interaction); and (3) computational decodification of EEG signals is not enough efficient (system side). In particular, active systems have been much more challengeable to set up since they depend on the user mental effort, rather than spontaneous neural responses as reactive systems do [7]. However, active systems can be controlled by "real" users' intentions since they do not depend on external stimulation as reactive systems do. Furthermore, mental tasks strengthen other neural mechanisms, apart from those related to mental task per se. A case in point is motor imagery (MI). MI refers to the generation and maintenance of imaginary movements. As MI is motor activity, mental tasks related to MI activate the central and peripheral nervous system almost to the same extent that actual movements do it [8–10]. This property of MI-related tasks increases the technical and clinical applicability of BMIs, as well as our interest to define the scope of the present chapter to MI-based BMIs.

Over the past few years, the user has been identified as the main component of the MI-based BMI structure, but who has been frequently ignored in the BMI design [11, 12]. According to [13, 14], there are three factors and three conditioners that directly influence the user performance in an MI-based BMI. See **Figure 2**. On one hand, *factors* have been categorized into (1) user state, (2) user traits, and (3) user conditions. A *user state* can be regarded as the result of many physiological and psychological processes that regulate brain and body in an attempt to put the individual in an optimal condition to meet the environment demands [15]. User state includes emotions such as mood, and cognition such as motivation, mastery, confidence, competence, self-efficiency, and fear. *User traits* refer to behavior, capabilities and abilities that define a person, including personality (tension and self-reliance), and cognitive profile (attention span, attentional abilities, attitude toward work, memory span, visual-motor coordination, learning style, and abstractedness). *User conditions* are associated with demographic information such as age and gender, and lifestyle such as playing music instruments, practicing sports, playing video games, typing, and full body movement either for working or entertainment. On the other hand, *conditioners* have been grouped in (1) user-technology relationship, (2) attention, and (3) spatial abilities. *User-technology relationship* is the level of computer anxiety and sense of agency that a user poses. Computer anxiety refers to the fear and tension produced by the use of technology, while sense of agency is the belief and feeling of being the entity who is causing an action. *Attention system* is responsible for maintaining a state of vigilance (alerting function), selecting information (orienting function), and managing mental resources, which are moreover limited (executive control). Finally, *spatial abilities* are considered the skill to generate, maintain, scan, and manipulate mental images. Spatial

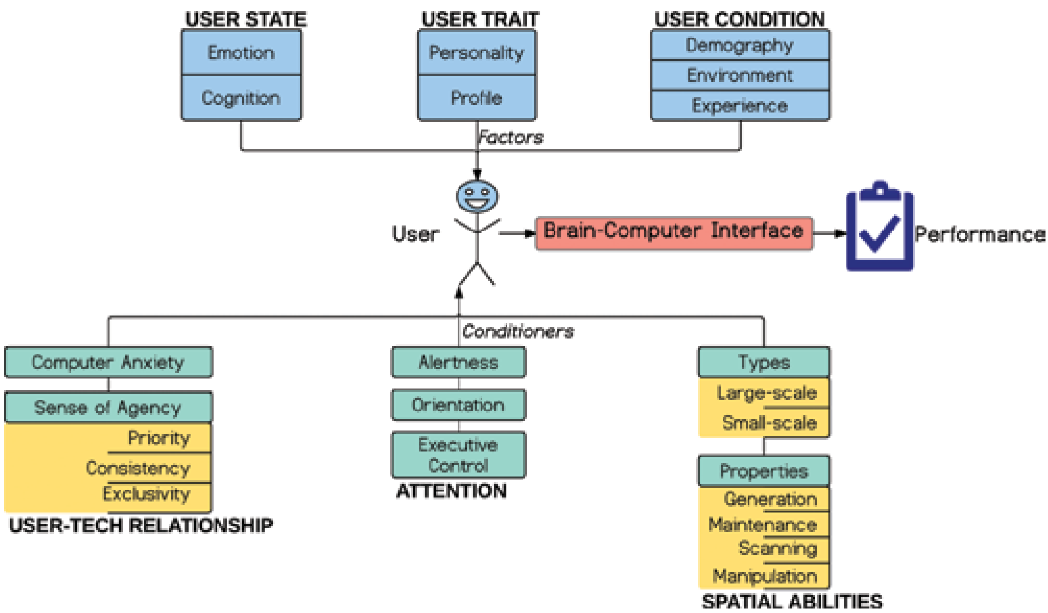

Figure 2. Factors and conditioners that directly influence the user performance during a brain-machine communication. This model has been constructed on the basis of the theoretical framework presented in [13, 14].

abilities can be of two types: small-scale and large-scale. Small-scale abilities refer to generate and transform small shapes and easy-to-handle objects, whereas large-scale abilities refer to spatial navigation [14].

As can be seen, evolutionary genetics, skill acquisition along lifespan, and sensory-cognitive information and resources determine the production quality of motor mental images, which in turn determines the modulation level of EEG signals used to decode user intentions. The modulation level of EEG signals due to MI activity defines if a good or poor brain-computer communication is established. On this basis, the present chapter gives an account of movement production (Section 2), provides an overview of neural oscillations associated with movement production (Section 3), and explores the ways in which humans produce movements (Section 4) so as to propose new training protocols based on how human learn, predict, and act (Section 5). MI is a skill that must be acquired, and possibly, an optimal way to fulfill this task is to lay down the same rules followed by humans when they interact with their environment.

2. Movement production

2.1. Generating movements

Most of the human behaviors involve motor function, which implies the complex and coordinated functional participation of several anatomic structures. The brain integrates the information from different sensory systems in order to construct specific internal representations of the environment. These representations allow the individual to organize, coordinate, and execute purposefully designed motor plans aimed to maintain internal stability and achieve different specific goals.

The motor plan is conceived in the cerebral cortex. The primary motor cortex, or M1, is located in the frontal lobe of the brain, and its main role consists in generating neural impulses that control the performance of movement on the contralateral side of the body. This is possible as M1 has a particular somatotopic representation of the body parts, in which those parts with more complex movements—e.g. hands—have larger representations. Moreover, the posterior parietal cortex, the premotor cortex, and the supplementary motor area also participate by using the visuospatial information to plan the complex movements and build a complex sensory guidance of each movement. These brain regions, commonly known as secondary motor cortices, send information to both primary motor cortex and brainstem motor structures in order to control the motor performance. They accomplish this goal acting on corticofugal neurons that give rise to corticospinal projections, the corticospinal tract, which ultimately end at striated muscle [16, 17].

On the other hand, the "basal ganglia" (striatum and globus pallidus) and related nuclei (subthalamic nucleus, substantia nigra, and pedunculopontine nucleus) constitute a group of subcortical nuclei primarily engaged in motor control, also playing important roles such as motor learning, executive functions and behavior, and emotions. These complementary pathways control posture and balance, coarse movements of the proximal muscles, and coordinate head, neck, and eye movements in response to visual targets. See **Figure 3** for illustrative purposes [18].

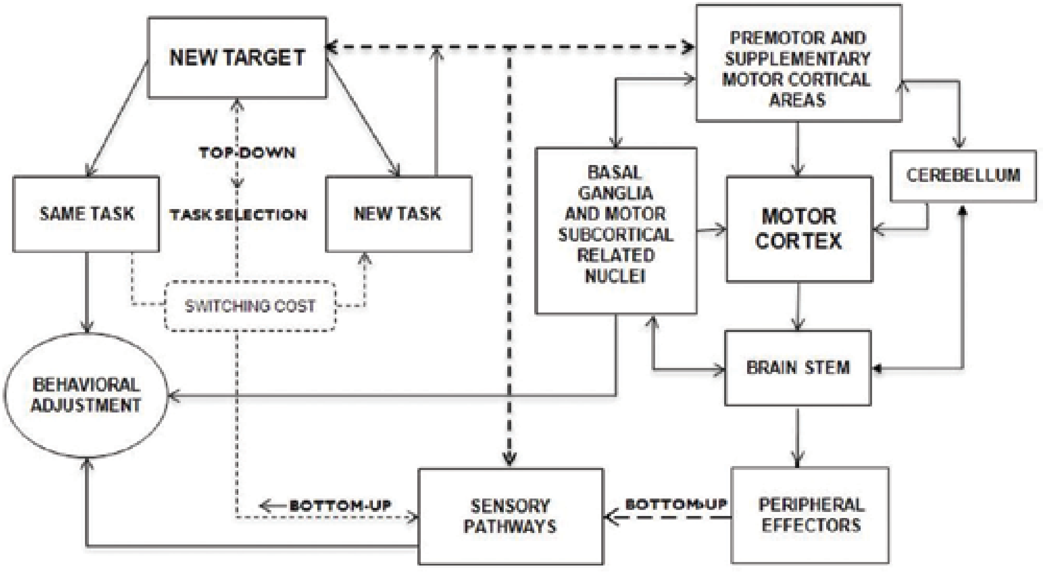

Figure 3. Schematic and simplified representation of the dynamic underlying a goal-directed movement, highlighting the most relevant neural substrates involved in this complex process. The term "switching cost" refers to the cost of adjusting the mental control setting to novel demands.

Despite the concurrence of multiple parallel loops and re-entering circuits that functionally engage complex temporary associations on an extended repertoire of neural structures, a regular movement is effortlessly carried out by healthy adults, due to the continuous converging streaming of visual, somatosensory, and postural information to the cerebral systems underpinning motor acts. In fact, the motor system is hierarchically organized in a way in which the primary motor cortex and several premotor areas crucial for planning and coordinating the sequence of movements are directly related with brain stem and spinal cord structures via neural projections. These relationships allow the upper brain structures to dynamically control the peripheral muscles, whereas several feedback circuits provide useful ascending information with the aim to maintain or adjust the motor commands if the situation demands it.

2.2. Categorizing the movements

In general, movements have been categorized as a) *reflexive*: involuntary coordinated patterns of muscle contraction and relaxation, predominantly based on spinal cord mechanisms; b) *rhythmic* (e.g. quadrupedal locomotion): repetitive motor patterns involving spinal cord and brain stem circuits, and c) *voluntary*: goal-directed mechanisms involving extended motor cortical areas, brain stem, cerebellum, basal ganglia, the pyramidal and extra-pyramidal pathways, among many others [19].

Learning refines the motor programs underlying voluntary movements. Several studies have shown significant changes in the anatomic maps of the motor programs through learning, usually referred as "implicit", a term used to define changes that cannot be explicitly described in general statements (e.g. to verbally explain the learning process of riding a bicycle).

2.3. Motor intention

During the last few years, generous empirical evidence has been gathered on the fact that goal-directed and non-goal-directed movements have different neural correlates. This simple distinction has enormous implications at the understanding of behavioral actions, and neurorehabilitation in general.

An essential challenge in the area of perception and motor control has been to identify the sensory-motor and cognitive processes associated with accurate goal-directed movements. In this context, it is important to note that motor behaviors are based on strategies developed over a lifetime of interacting with objects in the environment and that they are not always conscious strategies. They almost instantaneously ponder variables as body posture, cognitive evaluation, emotional attributes, and position of the target at movement initiation, trajectory and speed of the movement, gravidity effect, among several others.

The meaningful goal-directed movements have been studied in several contexts, sensory pathways, and using a wide variety of experimental tasks. However, a clear timeline delineating brain functional engagement to support these movements seems to be far from delineated.

Briefly, information from the spatial senses converges within the parietal cortex, where it is integrated and transformed into motor-relevant reference coordinates. This information is sent to the premotor cortex and integrated with information from prefrontal cortex about action goals and contexts before final motor output is sent to primary motor cortex, transmitted via the corticospinal tracts, and then modulated by the cerebellum and basal ganglia [20, 21].

The premotor regions have an important role to play in motor planning and the outlining of the motor sequence of the forthcoming goal-directed action. In this sense, a decreased activity in the parietal operculum has been correlated with activity in the lateral premotor cortex, the medial cingulate motor cortex, and supplementary motor cortices. In addition, the left dorsolateral prefrontal cortex, the anterior cingulate motor cortex and bilaterally, the insular cortices are also functionally involved [22, 23].

The cerebellum is another important region that is thought to represent the timing of our goal-directed actions. The neocerebellum has been found to relate with the control and planning of voluntary movements while the intermediate cerebellum seems to be involved in regulating the quality of the movement. It has been argued that the cerebellum is a key predictive component in the conceptualization of the internal models of motor control, probably due to its extensive projections, through the thalamus, to the premotor and prefrontal cortices [24].

2.4. Imagining a movement

Mental imagery is a multimodal construct supporting the formation and maintenance of inner representations of either previously perceived images or feelings, or foreseeing upcoming events in the absence of external sensory input. Within this framework, MI alludes to the dynamic state or mental representation of a given motor action that is rehearsed in working memory without any explicit motor act [25].

There is enough empirical evidence pointing out that imagined stimuli are treated in the same way as other direct sensory stimulations because they engage in multisensory interactions with stimuli directly perceived. In this regard, during real and imagined movements, brain functional activity seems to focus on related neural networks. It is not surprising then that MI draws on the similar neural circuits that are used in actual perception and motor control, involving networks associated with memory and emotion.

Depending on the MI task used, multiple neuroimaging studies have revealed the functional participation of motor, premotor, and supplementary motor cortices, which are consistently activated during motor imagery and are also major components of the interconnected network for motor intention. In addition, other structures play an important functional role in motor imagery as it occurs with the cerebellum, the basal ganglia, the superior and inferior parietal lobules, and the precuneus. Therefore, several authors have concurred in the notion that when performing MI, main differences with motor performance probably lie in the inhibition of some motor commands triggering movements [26].

2.5. Observing a movement

MI and movement observation (MO) have traditionally been studied as separate processes that activate the motor system without any actual motor execution. However, motor and perception action representations are closely interrelated to such a degree that perceiving another person's action triggers comparable representations as performing the action. This effect has been called "motor resonance."

In terms of neural substrates, evidence indicates that when observing a movement, there is a significant activation on caudal supplementary motor area, bilateral cerebellum and precuneus, but also involving the basal ganglia, the inferior parietal cortex, ventral premotor cortex, and left insula. On this subject, cortico-motor activity is significantly increased while combining MI and MO, compared to either MI or MO independently. This has led to the theory that they are both concurrent processes, in which action representation might be implemented by the dynamic interaction between perception and executive brain networks, thus opening interesting possibilities for practitioners in motor learning and rehabilitation settings [27–29].

2.6. Motor disabilities

Motor impairment—or physical disability—is a common outcome from a wide range of diseases and health conditions that affects almost one of eight adults in America. In broad terms, disability is understood as the inability to engage in any substantial gainful activity in view of confirmable physical or mental impairment(s), lasting for not less than 12 months. Physical disability encompasses limitations in individual physical functioning, mobility, dexterity, or stamina. They are rarely confined to a particular disturbance of motor capabilities and also impact psychological, social, economic, and the quality of life of the affected individuals [30].

Motor disabilities can be broadly divided into two major groups, according to their inflicting conditions: a) traumatic injuries and b) congenital conditions and diseases.

2.6.1. Traumatic injuries

There are several limitations subsequent to traumatic injuries that not only include motor impairments. Neurological sequelae can also involve cognitive impairments or sensory disabilities such as deafness and blindness post-neurotrauma, limb deformations or amputation, paralysis subsequent to spinal cord injury that can affect both arms and legs—quadriplegia, both legs—paraplegia, or a more unusual combination of the limbs.

2.6.2. Congenital conditions and diseases

Several congenital conditions such as cerebral palsy, muscular dystrophy, etc., can lead to different types of motor disabilities. In addition, several degenerative nerve diseases (e.g. Parkinson's disease, multiple sclerosis, amyotrophic lateral sclerosis/Lou Gehrig's disease, etc.), and other neurological conditions (e.g. stroke, central nervous system vascular accidents, peripheral neuropathies, etc.) can also produce different degrees of motor disabilities, even including an extreme form of motor impairment termed as "locked-in syndrome," in which voluntary control of almost all muscles is lost, yet retaining a normal cognitive functioning.

3. Neural oscillations in movement production and beyond

3.1. Overview

Sensory stimulation, cognitive activities, and motor behavior result in amplitude suppression or in amplitude enhancement of the EEG signals, depending on the degree of synchronization of the neural oscillations. Such degree of synchronization is reflected in various frequency bands. Moreover, the synchronization mechanism of the neural oscillations does not only reflect processing of physical and psychological events, but it also appears prior to the event occurrence. The association of this EEG modulation with specific events is known as event-related oscillation (ERO). EROs can be of two types: event-related synchronization (ERS) and event-related desynchronization (ERD). If EEG rhythms increase their synchrony and thus their amplitude, an ERS arises. Otherwise, an ERD appears. ERS reflexes awake-restful states, inhibition processes, rebound events, attention-related demands (e.g., attentive expectation of relevant stimulus omission, working memory activation, and episodic short-term memory task), and cognitive-mnemonic processes. Oppositely, ERD is involved in the processing of sensory and cognitive information, and production of motor behavior [31, 32].

EROs are characterized by four parameters: spatial location, magnitude, latency, and reactive frequency band. Among those parameters, the frequency is the key parameter to understand how humans interact with their environment. Historically, neural oscillations have been studied into five frequency bands: delta, theta, alpha, beta, and gamma [33].

3.1.1. Delta band oscillations

Delta band oscillations (below 4 Hz) are indicative of deep sleep in adults and appear during long attention tasks [34]. They have been also found to carry information pertaining to different movements around a joint, such as extension and flexion of the wrist [35].

3.1.2. Theta band oscillations

Theta band oscillations resonate at the frequency band 4–8 Hz and emanate from the frontal midline due to audio-visual information encoding, attention demands, memory retrieval, and cognitive load. Moreover, these oscillations enhance after practice on the cognitive tasks at hand. They are more prevalent when the individual is focused and relaxed, and prolonged activity is related to selective attention [33, 36]. The upper theta band (6–8 Hz) is also known as lower-1 alpha band and generally reflects levels of alertness [31].

At a neurophysiological level, anticipating sensory events resets the phase of slow, delta-theta (2–8 Hz) activity before the stimulus occurs [32].

3.1.3. Alpha band oscillations

Alpha band rhythms oscillate at frequencies between 8 and 12 Hz and may come from frontal, temporal, parietal, and occipital regions. Overall, enhancement and suppression of alpha band rhythms are respectively associated with top-down and bottom-up information processing [37].

According to the functional roles of the alpha band rhythms, they can be categorized into mu, occipital, and tau rhythms. Mu-rhythms (or sensory-motor rhythms) arise from the sensory-motor cortex at both bandwidths 8–12 and 16–24 Hz. Enhancement and suppression of mu rhythms are due to sensory stimulation, motor activity, cognitive processes, and emotional influences [31]. Particularly, synchronization of mu rhythms increases in line with attention demands, sensory encoding, inhibition processes, and rebound events. On the other hand, suppression of mu rhythms responds to complexity, level of difficulty, and relevance of the tasks in progress. The nature of the task is reflected on the bandwidth reactivity. For example, general tasks associated with arousal, attention, effort, and expectancy produce lower alpha (8–10 Hz) desynchronization widespread over the whole scalp. In contrast, specific tasks related to information processing, selective attention, and motor activity elicit upper alpha (10–12 Hz) topographically restricted desynchronization [31, 38, 39]. Note that "information processing" refers to feature extraction, stimulus identification, and response preparation. Occipital alpha rhythms respond to mental effort expended on the processing of visual relevant stimuli. Maximum suppression of occipital alpha rhythms is expected between 200 and 300 ms after stimulus onset. The ERD effect moves toward parietal regions, reaching a longer duration than the one reached over occipital regions, particularly within the lower alpha frequency band [33].Tau alpha rhythms (or mid-temporal third rhythms) have been associated with auditory stimulation, and are obviously expected over the temporal lobe. However, these rhythms are hardly recorded over the scalp owing to the anatomical limitations [31].

3.1.4. Beta band oscillations

Beta band oscillations function as a resetting mechanism, which permits neural networks to work repeatedly. These oscillations also play an important role in the top-down process that takes place during predictions [32]. According to their topographical origin, they can be identified as central, frontal, and occipital beta band oscillations. *Central beta band oscillations* are related to cognitive-motor tasks, and relaxation states preceded by strong activations. *Frontal beta band* mainly oscillates around 19 Hz, are post-stimulus events, and are associated with stimulus assessment, level of difficulty, and decision making. Finally, the *occipital beta band rhythms* occur in response to visual stimulation followed by mental relaxation [33].

3.1.5. Gamma band oscillations

Gamma band rhythms oscillate near 30 Hz during linguistic processing of meaningful words and near 40 Hz during sensory encoding, perceptual-cognitive functions, and motor behaviors. With regard to 40 Hz-rhythms, these are phase-locked to the stimulus and short-lasting, and appear 100 ms post-stimulus in sensory-motor tasks. In contrast, these are induced and late-appearing oscillations that might achieve maximum synchrony over the fronto-central region in perceptual-cognitive tasks [36, 40, 41].

According to [32], while predicting when predominantly involves low-frequency oscillations, predicting what points to a combined role of gamma and beta oscillations.

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3.2. EROs in voluntary movements

Voluntary movements are produced in three phases: planning, execution, and recovery. During the three phases, voluntary movements provoke EROs within alpha, beta, and gamma bands. These EROs are also generated in the course of imaginary movements to some extent. In this section, the generation of EROs during voluntary movement is first explained, and then how these EROs are reproduced during MI is described.

3.2.1. ERD within the upper alpha band

Voluntary movements result in a somato-topically specific and topographically restricted desynchronization of the upper alpha band over the sensory-motor cortical area. This desynchronization starts around 2 seconds prior to movement onset over the contralateral side and becomes bilaterally symmetrical immediately before execution of movement. This ERD shows a slow recovery in the period of 2 or 3 seconds following the movement [42].

3.2.2. ERS within the upper alpha band

During movement preparation and execution, desynchronization of the upper alpha band is often accompanied by ERS over occipital areas. This ERS can also appear after movement over areas that displayed ERD before. It has been hypothesized that this ERS is produced by deactivated cortical areas. The ERD/ERS effect within the upper alpha band is known as focal ERD/surround ERS [43].

3.2.3. EROs within the Rolandic beta band

Desynchronization of the Rolandic beta band starts around 1 second prior to movement onset over the contralateral sensorimotor area, becoming bilaterally symmetrical during movement execution. This beta ERD recovers in less than 1 second, much faster than upper alpha ERD. After the beta ERD recovery, an ERS around 20 Hz appears. Note that this beta ERS occurs while the upper alpha ERD exists. This post-movement beta ERS is a relatively robust phenomenon because it has been found after finger, hand, arm, and foot movements. However, it is larger in hand movements. The beta ERS is dominant over the contralateral primary sensorimotor area and has a maximum around 1 second post-movement [43].

3.2.4. ERS within the gamma band

It has been found that voluntary movements also provoke ERS within the gamma band. Gamma reactivity is predominantly generated over the primary sensorimotor area. The location of gamma ERS varies with type of movement, i.e., it is somato-topically distributed. Gamma ERS appears as a sharp power increase around 36 Hz shortly before movement-onset. However, this is rarely found in the human EEG. Gamma ERS also reveals a maximum around 40 Hz during execution of movement. This ERS is considered as a stage of active information processing [44].

3.3. EROs in imaginary movements

As MI relies on the same mechanism as actual movements, it is not surprising to observe similar EROs during imaginary movements. Specifically, upper alpha ERD during MI is very similar to upper alpha ERD observed during the planning phase of motor executions, i.e., it is locally restricted to the contralateral sensorimotor areas. In both cases, ERD may reflect a type of readiness or pre-setting of neural networks in sensory-motor areas. Similarly, Rolandic beta ERD appears during MI as it does during movement preparation. After the MI activity, the Rolandic beta ERS found post-movement over the pre-central region of the brain is reflected as well [43, 44]. These EROs are illustrated in **Figure 4**.

3.4. Neural oscillations in BMI

As was aforementioned, a BMI is an emerging technology that aims to achieve interaction between humans and their environment by making use of their neural oscillations. In order to establish brain-machine communication, systems can employ MI-related mental tasks to modulate user neural oscillations, and thus extracting wealthy information to generate an action. As was discussed in this section, MI activity produces well-established ERD/ERS patterns, which have been moderately used to control BMIs. However, it is also well-known that MI-based BMIs require long training sessions and are not suitable for all people [45–47].

From **Figure 2**, it can be clearly seen that the level of synchronization of neural oscillations depends on a wide variety of factors and conditioners. The human-environment interaction through BMI engages a large number of sensory, cognitive, and motor processes, which modulate neural oscillations beyond the MI-related mental tasks. Typically, BMI users are rigorously trained to dominate MI skills, so as to magnify the ERD/ERS effects on the scalp, regardless of evolutionary genetics, skill acquisition along lifespan, and sensory-cognitive information and resources at a time (**Figure 2**). BMI is not only associated with the analysis of EEG signals prior to, during and after MI activity [48–50], but it is also related to previous knowledge of user, current user state, user profile, and environmental conditions: factors that determine the level of synchrony of neural oscillations as well.

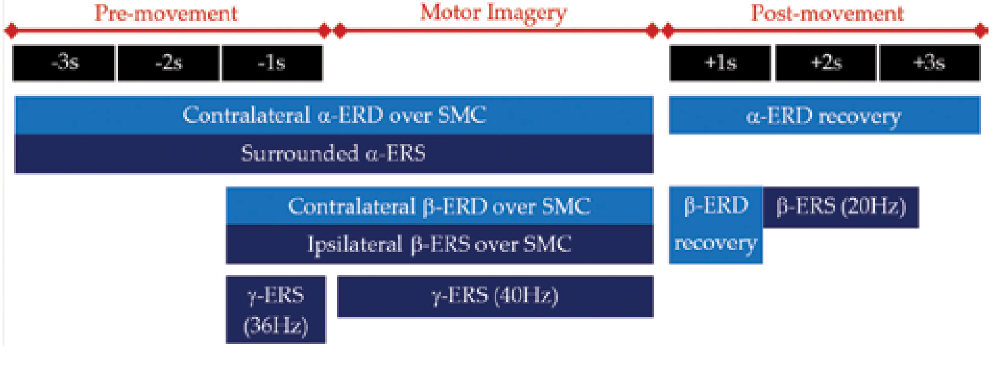

Figure 4. Neural oscillations in MI activity. Similar to voluntary movements, MI is produced in three phases: planning, execution, and recovery. During the three phases, MI modulates neural oscillations in alpha, beta, and gamma bands.

4. Sensory-motor system in motor skill acquisition

Movement is the means whereby individuals interact with other individuals and their environment. Most of motor information is gathered along the human lifetime, but there are also few motor skills genetically and evolutionarily inherited. In general, movements are skills acquired by learning, and are the result of transforming sensory and cognitive inputs into motor outputs. As motor system is a complex mechanism trained along lifetime, and MI-based BMI attempts to decode motor intentions from neural oscillations in order to put a device into action, motor mechanisms should be considered when prototyping BMI systems. Understanding motor processing and control, and including thereafter such motor mechanisms in the BMI architecture could lead to solve BMI drawbacks at the source. On this basis, the main issues addressed in this section are: (1) how humans execute movements, (2) relevance of somatosensory information in movement processing and control, and (3) the role of MI in sensory and motor systems.

4.1. Modular selection and identification for control (MOSAIC) model

Movements are skills that humans need to acquire along with their life-time through an error-and-trial process, which depends on the reduction of kinematic (geometry and speed) and dynamic (force) error detected through somatosensory channels, primarily visual and proprioceptive ones. Eventually, movements become habitual behaviors.

To produce a movement, prediction (forward model) turns motor intentions into expected sensory-cognitive consequences, whereas control (inverse model) turns desired consequences into motor commands. This model is known as modular selection and identification for control (MOSAIC) model. The transformation from sensory-cognitive into motor signals according to MOSAIC model is as follows. Firstly, motor behavior patterns are predicted according to previously acquired knowledge (memory), and simultaneously, sensory predictions are made by scanning the working environment (context). Secondly, motor behavior patterns and sensory predictions are used to make a motor prediction. Thirdly, those predictions are turned out to be movements, and thereby modifying the working environment. Finally, environmental changes cause sensory feedback used to adjust motor behavior [51, 52].

Motor system depends on several forward models that run simultaneously. Each of those forward models is paired with a corresponding inverse model as is illustrated in **Figure 5A**. Note that the controller of the inverse model weights its output in accordance with the matching between sensory feedback and motor prediction. In this way, every forward-inverse model pair contributes correspondingly to motor execution, and depending on the environmental demands [53].

4.2. Sensory feedback in the motor system

Sensory feedback, result of environmental changes caused by motor execution, is not only compared with motor prediction to readjust motor execution. Sensory information collected from the working environment also leads to perceptual learning. From **Figure 5A**, it can be seen that sensory information feed forwards the forward model. This means that sensory

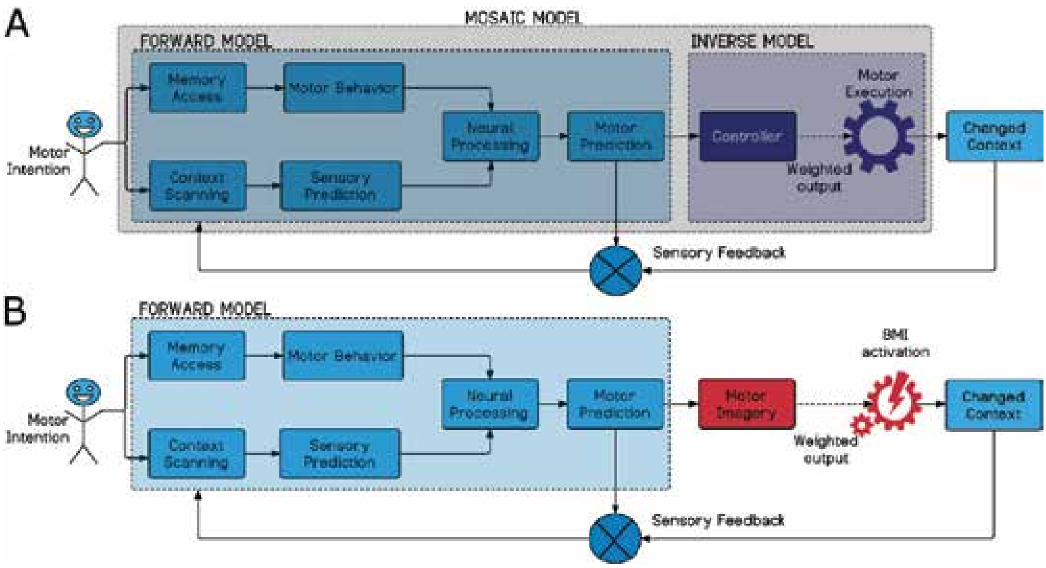

Figure 5. Motor system according to the modular selection and identification for control (MOSAIC) model, and sensory feedback. (A) System diagram to execute actual movements. (B) System diagram to achieve interaction with the environment through MI-based BMI by both sensory and motor systems.

feedback is used to make new sensory predictions, and it influences motor behaviors. As learning is a process that involves changes in behavior that arise from interaction with the environment [52], it means that sensory feedback does not only confirm or contradict motor prediction, but it also promotes perceptual learning.

Recent neuroimaging evidence suggests that perceptual learning promotes neural plasticity over sensory-motor cortices, and increases connectivity between such areas of the brain. Furthermore, the effect of perceptual learning is durable [54, 55]. This means that somatosensory function plays a vital role in motor (re) learning. As motor skill (re) acquisition is determined by sensory and motor systems, MI-based BMIs should be designed in terms of both systems. At present, only motor system is considered in the BMI architecture. However, if sensory feedback is properly given, perceptual learning will be gained, which in turn will achieve the acquisition of MI skills.

4.3. Motor imagery as a result of sensory and motor systems

Up to now, MI as control task in BMIs has been seen as a skill that must be acquired, but neither user conditions nor controlled learning conditions have been taken into account. Only recently, when MI-based control has not been achieved by anyone at any time [7, 11], those two conditioners started to be investigated [14].

Turning now to **Figure 5B**, it can be seen that MI is managed by forward models, fact that has been shown in previous neurophysiological studies [56, 57]. This indicates that MI depends on sensory predictions and motor behavior patterns, proceeding respectively from context scanning and previous knowledge. As is illustrated in **Figure 2**, previous knowledge of users

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(encompassed under the user condition category) influences directly user performance. To date, user ability to produce motor mental images has been somehow quantified psychologically and neuro-physiologically to evaluate the user potential to control a MI-based BMI [13]. However, the role of context, along with sensory prediction, has been overlooked. Based on **Figure 5B**, the production of imaginary movements depends on both motor repertoires built along lifetime and environmental conditions. Furthermore, if a MI-based BMI attempts to put into action MI tasks, the resulting environmental changes will necessarily produce sensory feedback that must be collected, and then, provided to the forward model in order to readjust MI activity. That is, MI is a mental rehearsal that proceeds from forward motor model, which is intended to be effected through BMI, and which should be readjusted by sensory feedback. Following this line of though, it is proposed to restructure current training paradigms used to train BMI users on the basis of forward model, sensory feedback, and perceptual learning.

5. Toward training paradigms based on how human learn, predict, and act

The interest on MI-based BMIs has been growing exponentially. Although the idea of direct brain-machine communication is very attractive stand alone, BMIs as a tool in Neurosciences to investigate sensorimotor transformations of the nervous system has magnified BMI research [58]. So far, the major issue to debate in BMI research has been system performance. As has been herein discussed, user conditioners and factors are closely associated with system performance (**Figure 2**), and in turn, all those conditioners and factors are related to the acquisition of MI skills. If imaginary movements became automatic, brain-machine communication would be natural and efficient. It is hypothesized that the best way to acquire MI skills is following the same rules humans obey to move around the world. Hereunder, new training paradigms based on the sensory-motor system are proposed.

5.1. How to design new paradigms based on the sensory-motor system functioning to achieve MI skill acquisition?

Similar to actual movements, imaginary movements are predicted in line with motor repertoires built along lifetime, and sensory predictions made through context scanning (**Figure 5B**). Therefore, the first step to design a training paradigm is to create a favorable and familiar environment, which provides at a first glance the sufficient sensory information about which imaginary movements are needed to interact with such environment. This first step refers to the creation of an *ecological environment*. The second step is to identify the necessary imaginary movements in line with the nature of the working environment. Note that the selected imaginary movements are used to modulate EEG signals, and thus getting control of the system. For this reason, the selected imaginary movements are known as *control tasks*. The third step is to modify the working environment as if imaginary movements were being actually executed. This achieves consistency between what is imagined and how that mental image is effectuated. Frequently, the set of imaginary movements that user performs to establish brain-machine communication is not strongly related to the control panel of the system. For example, imaginary movements of mouth, foot, left hand and right hand are often mapped respectively to move forward, move backward, turn left and turn right. This kind of mapping causes confusion, and makes difficult the user-system adaptation, since not only MI skill acquisition is necessary, but also the correlation between mental rehearsal and control panel. The consistency between imaginary movements and control mechanisms is referred to as *transparent mapping*. Finally, the last step is to provide *sensory feedback* to obtain perceptual information about the environmental changes effected by the MI activity in use.

By way of illustration of this MI training paradigm, the following scenario is constructed. If the working environment is a photo album on a mobile, and the interaction task is to slide photos, the control task should be to imagine sliding the index finger from left to right. With respect to sensory feedback, this can be given in three modalities: (1) auditory, playing a sweeping sound while the current photo is being replaced by the next one; (2) visual, sliding from one photo to another; and (3) tactile, producing a vibration in the hand of interest, similar to the one perceived from mobile devices. The MI training paradigm, along with this exemplification, has been outlined in **Table 1**. The complete picture (forward model, MI process, neural oscillations, and sensory feedback) of this scenario is provided in **Figure 6**.

It is worth noting that there are several neural oscillations related to MI process (**Figure 4**); however, in **Figure 6**, only those previously estimated to improve BMI performance were considered. In [48, 49], it was found that pre-stimulus sensory-motor rhythms can predict user performance, and can lead to better classifiable EEG patterns as well. In [50], it was demonstrated that the most optimal features to differentiate MI tasks were post-MI period, rather than peri-MI period. Nevertheless, the signal analysis is not limited to this proposal.

5.2. Why should these paradigms increase MI-based BMI performance?

These new MI training paradigms take advantages of previous knowledge of users since they supply meaningful contexts. These paradigms can facilitate the generation and maintenance of mental image due to the automatic development of sensory predictions and motor behavior

Step		Description	Exemplification
❶	Ecological environment	Create a favorable and familiar environment, which provides at a first glance the sufficient sensory information about which imaginary movements are needed to interact with such environment.	Photo album on mobile.
❷	Control task	Identification of control tasks according to the ecological environment.	Slide index finger from left to right.
❸	Transparent mapping	Consistency between imaginary movements and control mechanisms.	Slide photo from left to right.
❹	Sensory feedback	Multisensory feedback in order to perceive environmental changes.	Sweeping sound, tactile sensation, virtual hand.

Table 1. Motor imagery training paradigm based on motor prediction mechanisms (forward model of motor system) and sensory feedback.

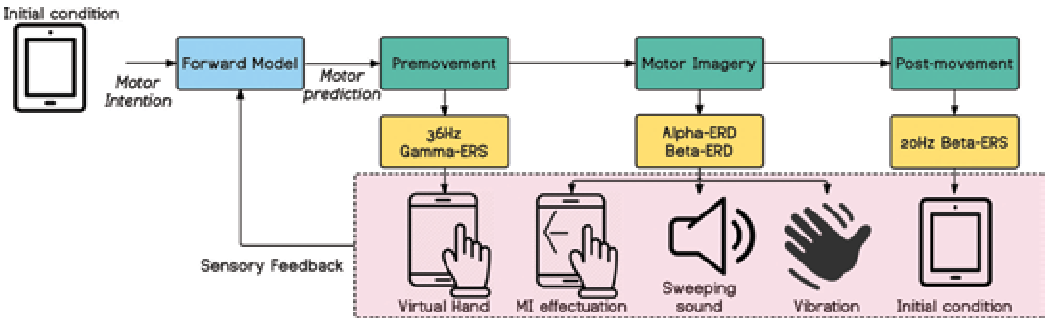

Figure 6. MI training paradigm based on the forward model of the motor system, MI process, neural oscillations, and sensory feedback.

patterns in the brain. Furthermore, the effectuation of MI as an actual movement will make users feel that their mental images are being executed, and are changing their working environment. The external changes give sensory feedback to users, which allows forward model readjusting the imaginary movement in course.

On the other hand, the present MI training paradigms can help to reduce *computer anxiety* since users are interacting with commonly used devices inside a familiar context. They can also increase *sense of agency* since what they imagine is what is executed, and even more, they feel it. *Attention* could increase as well, since users are doing what they like to do. Moreover, if the ecological environment is personalized for each user, attention could be even higher. Finally, at the time of selecting small-scale *spatial abilities* related to activities of daily living, the generation and maintenance of mental images can be facilitated.

6. Conclusion

The interest on MI-based BMIs has been growing exponentially. Although the idea of direct brain-machine communication is very attractive stand alone, BMIs as a tool in Neurosciences to investigate sensorimotor transformations of the nervous system has magnified BMI research. Of particular interest is the neural mechanism behind the motor system, because movement is the only way human beings have for interacting with the world. When this system is malfunctioning, people eventually or suddenly lose their autonomy, what leads to overcome several socio-economical pitfalls. Only in Mexico, around 15.9 million people have some kind of limitation, either mental or physical. This means that 6% of the total population in the country has a poor quality of life. According to the National Institute of Statistics and Geography (2014), mobility restrictions are the most recurrent disability and they are typically associated with aging process, traumatic injuries or congenital conditions.

Unfortunately, MI-based BMIs are still a laboratory prototype since not anyone at any time can control the system. The system functionality greatly depends on the modulation of EEG signals by means of MI-related tasks. MI as control task in BMIs has been seen as a skill that must be acquired, but neither user conditions nor controlled learning conditions have been taken into account. In this chapter, it has been proposed new training protocols based on how human learn, predict, and act. Possibly, an optimal way to master MI tasks is to lay down the same rules followed by humans when they interact with their environment. This can reduce computer anxiety, increase sense of agency and attention, and facilitate the acquisition of small-scale spatial abilities.

Conflict of interest

No conflicts of interest are declared by authors.

Author details

Luz Maria Alonso-Valerdi[1]* and Andrés Antonio González-Garrido[2]

*Address all correspondence to: luzalonsoval@gmail.com

1 Escuela de Ingeniería y Ciencias, Tecnológico de Monterrey, Monterrey, N.L., México

2 Instituto de Neurociencias, Centro Universitario de Ciencias Biológicas y Agropecuarias, Universidad de Guadalajara, Guadalajara, Jal., México

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Chapter 6

Computational Models of Consciousness-Emotion Interactions in Social Robotics: Conceptual Framework

Remigiusz Szczepanowski, Małgorzata Gakis,
Krzysztof Arent and Janusz Sobecki

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Abstract

There is a little information on how to design a social robot that effectively executes consciousness-emotion (C-E) interaction in a socially acceptable manner. In fact, development of such socially sophisticated interactions depends on models of human high-level cognition implemented in the robot's design. Therefore, a fundamental research problem of social robotics in terms of effective C-E interaction processing is to define a computational architecture of the robotic system in which the cognitive-emotional integration occurs and determine cognitive mechanisms underlying consciousness along with its subjective aspect in detecting emotions. Our conceptual framework rests upon assumptions of a computational approach to consciousness, which points out that consciousness and its subjective aspect are specific functions of the human brain that can be implemented into an artificial social robot's construction. Such research framework of developing C-E addresses a field of machine consciousness that indicates important computational correlates of consciousness in such an artificial system and the possibility to objectively describe such mechanisms with quantitative parameters based on signal-detection and threshold theories.

Keywords: social robot, consciousness-emotion interaction, machine consciousness, signal-detection theory

1. Introduction

It is widely acknowledged that a social robot should be an embodied agent which can communicate with people easily, using both verbal and nonverbal signals [1]. Such a robot needs to have a wide range of social and cognitive skills [2, 3] to understand human behavior and to be intuitively understood by people. However, it should be noted that nowadays there is a gap between the requirements concerning a social robot and their implementations. It is due to imperfection in technology and deficiencies in theory in various areas ranging from psychology through computer science up to classical robotics. Despite of intense technological efforts over the last two decades in terms of developing high-level cognition models for human-robot interaction (HRI), so far, robot's constructions have been hardly equipped with such competency. Here, we focus on issues concerning development on processing the interaction between consciousness and emotions in a social robot.

2. Designing human-robot interaction

Designing efficient HRI is a basic research problem of modern social robotics [1, 4]. This is mainly due to a technological struggle to make a construction of robots that is intended to share space with humans and support them in daily life in a socially acceptable manner. The joint efforts of modern research including cognitive psychology, developmental psychology, philosophy of mind, and modern technology such as artificial intelligence and machine learning show that creating effective HRI depends on the implementation of human high-level cognition into a robot's system. For example, emotions in the context of social robots have attracted a considerable attention for the last two decades [5]. It is expected that artificial emotions increase plausibility of interactions including predictability of a robot behavior. The well-known idea of a "theory of mind" describing our ability to mentalize others' internal states was captured by theoretical accounts by Baron-Cohen [6] and Leslie [7] and finally was used to construct a Cog humanoid robot with the usage of current technology [3]. In addition, endowing of a robot in a theory of mind [3] could allow the robot to detect, recognize, interpret, and react to a human behavior and hence to make interaction more human-like. There are a lot of works concerning emotions, computational models of emotions in psychology, and computer science, but there is no result to date that would considerably improve a social robot behavior. Attempts to implement and verify a computational model of emotions in a control system of a real robot have been undertaken systematically for many years. For example, emotional system of Kismet designed from scratch is strongly inspired by various theories of emotions in humans [2]. An affective, computational model of mind fearnot affective mind architecture (FAtiMA) [8] was implemented in the robot FLASH [9]. The works in [10–12] are examples of systems that were verified using agent-based modeling software and possess a potential in the context of implementation in robots. The experience gained to date points to three areas of challenges.

Nowadays, sensory systems of robots are insufficient to detect social events, such as human emotions, intentions, attention points, etc. Clear and natural expressing of emotions and other internal states by a robot requires advanced and expensive mechatronic solutions. Computational model of consciousness and emotions can be interpreted as compound components of a higher level part of the robot control architecture. Therefore, implementation of such models requires them to be formally complete and adequate that is not guaranteed by the current psychological research.

3. Consciousness-emotion interaction as functions of the human brain

Philosophy of designing robotic systems inspired by human high-level cognition, including attentional and perceptual processes, is commonly used and known as a biologically inspired approach (see [11–13]). Some studies have also indicated the possibility of implementing into the social robot a computational architecture, which is inspired by a neurobiological basis of the brain [14]. For instance, there are well-developed robotic control systems of high-level cognition that implement a feature-integration theory of attention [15] or a model of saliency-based attentional search mechanisms [16] that have been intensively verified both behaviorally and computationally [13].

Contemporary brain research suggests that the interaction of cognition and emotion may be crucial for a social robot's design [14, 17]. For instance, Pessoa [14] argues that the fundamental problem is to determine an organization of the robotic system in which cognition and emotion are intertwined in a general information-processing architecture. In general, such information-processing architecture should be viewed as a general theory that describes important components of the system and relations between such components [18]. In this way, the adopted architecture can determine an organization of the cognitive system and general principles of information processing in the robotic system. Therefore, goal-directed or conscious behavior of a social robot in terms of recognizing human affective states will require understanding how complex cognitive and affective processing should be mapped into a robotic information-processing system that performs computational algorithms to integrate C-E interactions effectively as the human brain does it. In fact, brain research indicates that there is no decisive evidence what kind of organization of information processing is ultimate to mediate the C-E interaction effectively. Many neuroscientists (see [19, 20]) indicate that there is a functional division in the brain between low-level processes of emotion regulation (for instance, linked with amygdala activation) and higher order processes that are associated with frontal and parietal cortical activity involved in conscious goal-directed behavior. In addition, according to modern neurobiological accounts (see [21]), the amygdala synchronizes and modulates access to affective stimuli in such a way that their representations are stronger (exert a stronger influence on behavior) than neutral stimuli. Thus, selection of specific architecture can determine how a specialized C-E interaction system should be organized; it should also enable to define specific components of such system that are attributed to specific brain structures as well as describe how computations underlie high-level cognitive processes underlying such interaction. Following this line of reasoning, it is possible that the architecture of the C-E interaction in the social robot may be either structured into blocks (a theoretical system that processes sequentially, in which the knowledge is hierarchical, etc.), or modules (there are independent, autonomous, distributed modules handled by a central processor, e.g. [22]) or represents some kind of non-modular organization in which information processing is inspired by neurocomputations for which simple interactions between processing units are going on [23]. It is therefore important in terms of social robots to set up theoretical criteria to analyze potential architecture of the C-E interaction in the brain regarding structural components and functionality of the social robot's system.

4. Consciousness-emotion interaction and machine consciousness approach: establishing formal assumptions

Besides specific architecture of cognition for social robots, the essential problem of designing effective HRI is to analyze conscious behavior of the robot by considering human conscious knowledge and therefore considering subjectivity experience that accompanies consciousness (phenomenal aspects of consciousness; see [24, 25]). In our opinion, such a research problem should be embedded within the area of machine consciousness that can identify critical computational correlates of consciousness [26] to establish HRI. According to this computational approach, consciousness and its subjective experience can be explained by higher level cognition that is grounded in neurocomputations in the brain [25]. This approach not only allows for development of machine consciousness but also attempts to explain a so-called hard problem of consciousness that is related to inability to objectively measure phenomenal aspects of consciousness (see [27]). In fact, the theories of machine consciousness have been successively implemented in artificial environments (e.g., system CLARION; see [28]); some attempts were made in terms of implementing them into robotic systems [29].

Given such philosophical physicalism [30], we assume that consciousness of the robot can be addressed within an information-processing framework in terms of behavior control, information integration, attention and access to the information, or ways of expressing internal states of the robot. According to this framework, social robots are embodied, socially intelligent agents, operating in the human environment [1, 11, 12]. Our conceptual framework attempts to solve the problem of modeling consciousness-emotion interactions using the machine consciousness approach. Below, we will demonstrate that feasibility of hypothesized computational correlates of consciousness for the C-E interaction in a social robot system is formally allowed within on a signal-detection theory (SDT) [31] and a threshold theory [32, 33].

5. Modeling consciousness-emotion interaction using a combination of signal-detection and threshold approaches

According to Reggia and colleagues [25], the machine consciousness approach indicates that a possible computational correlate of consciousness is representational property defined as a possible way of encoding incoming information in the cognitive system. It is postulated in this account that such representations may be a pattern of neuronal activity that is encoded in the current states of the neuronal network [34]. For example, in a study on visual awareness with backward masking [35], patterns of conscious behavior are described as human ability to detect emotion under a forced-choice condition within a series of signal (e.g., mimic fear expression) and noise trials (e.g., neutral face expression) (see [36]). The assumption that consciousness is the ability to differentiate signal from noise based on choice behavior has enabled researchers to use a signal-detection theory (SDT) to quantify consciousness of emotion with objective sensitivity parameters [37]. It is therefore clear that conscious behavior identified with the SDT parameters can be used as a computational correlate to determine objective representations of the C-E interactions in the social robot's construction.

The computational approach to consciousness [25] also points out that an additional potential computational correlate of consciousness is represented by relational properties between the components of human knowledge. According to Reggia and colleagues [25], assumptions of higher order theory (HOT) of consciousness [36] nicely fit with this computational aspect. In particular, HOT postulates a computational correlate of consciousness which is the relationship between stimulus representation and its corresponding subjective knowledge of being conscious of the first-order representation (metarepresentation) [25]. In fact, modeling studies of consciousness and emotion [33, 37] showed that an adequate computational approach which considers the relation between consciousness and emotion can be described within the SDT framework. Szczepanowski [33] with his original proposal has shown that the SDT computational model may consider the fact that consciousness and emotions interact with one another. In addition, such computational SDT model of consciousness allows for a hierarchy of the information processing associated with conscious detection of emotion, that is, higher order processing requires prior discriminations of emotion at the lower level. This suggests that the relational relationship between the components of knowledge underlying architecture of the C-E interaction could be crucial for a social robot's design.

The machine consciousness framework also indicates that consciousness is characterized by a specific information-processing mode [25, 38]. Some theoretical accounts emphasize effectiveness of such conscious processing, and it has been argued that the information content in conscious state is processed globally [38]. For instance, Dehaene [39] who is an advocate of such line of reasoning has shown that global processing in the brain may be linked with activation of extensive long-distance neuronal connections that link several separate brain areas, including prefrontal areas that are not activated in another processing mode [38]. Indeed, such conscious processing mode may stand for a computational correlate of consciousness that explains the nature of conscious access that involves subject's disposition to action and mobilizes and integrates mental functions that operate independently and differ in terms of tasks under the unconscious condition [38]. In the context of conscious affective processing, it seems likely that activation of the global processing mode may operate on an "all-or-none" or discrete fashion when emotional stimuli enter consciousness [37, 40]. In fact, Szczepanowski [33] based on a Krantz threshold theory [32] demonstrated that preferences for affective representation to access consciousness may be the threshold processing. Thus, preferential conscious processing of emotion in the brain may arise from the fact that activation strength of affective stimuli to enter consciousness is characterized in the discrete manner [33, 37, 40]. This implies that in the case of affective information, the robotic system could be implemented with the global processing mode based on thresholds to be able for handling effective and natural HRI.

Thus, with the abovementioned assumptions, our conceptual framework shows that the computational organization underlying the C-E interaction in the robotic system should correspond to an architecture of affective computing in the brain [14, 41] and should be based on computational correlates of consciousness [25] by including (i) a low-level representation correlate which enables robot's objective conscious perception of emotion, (ii) a metacognitive correlate of robot's subjective knowledge of emotion, and (iii) a conscious processing mode based on global access to the emotion content. Here, we will explain in detail the idea of modeling computational correlates of C-E interactions with mathematical frameworks.

6. Signal-detection theory to encode objective consciousness of emotion in a social robot

The SDT theory assumes that the ability of human subject to perceive a stimulus is described by the probability of deciding whether a signal or noise stimulus was presented in a given trial [31]. The fluctuations of a stimulus presented within series of trials, for example, manipulated with a time exposure, or visibility of the stimulus, are determined by Gaussian probability density functions [31, 33, 42]. Because of presentations of two stimulus types under the forced-choice detection condition, participant within experimental condition produces correct (a hit (*H*) and correct rejection (CR)) and incorrect responses (a false alarm (*FA*) and miss (*M*)). The ability to detect a stimulus is then described by a sensitivity parameter $d'_{\text{Type I}}$, which conceptually corresponds to a difference in mean values from the probability distributions for the signal and noise. In addition to the sensitivity measure, the detection theory also provides a bias measure $c_{\text{Type 1}}$, which determines the participant's tendency to favor either "yes" or "no" responses during the detection process. Based on probability distributions, the receiver operating curve (ROC) is computed whose course determines the participant's ability to detect stimuli. According to the SDT, the task performance above the chance level will indicate conscious perception as measured by a significant nonzero sensitivity index ($d'_{\text{Type I}} > 0$). Similar conclusions are formulated when a size of the area under the ROC curve is above the level of 0.5 which is characterized by the so-called parameter $A'_{\text{Type 1}}$. In fact, according to Lau [42], the SDT sensitivity measure of consciousness in detection tasks is not sufficient and in terms of consciousness, it is important to determine decision criteria for detecting a stimulus based on the c parameter rather than discrimination ability per se. For instance, the SDT interpretation of behavior in blindsight patient with visual cortex damage who deny any visual sensation in the resultant visual field defect but can nonetheless detect the visual emotion stimuli presented in the area [43] would indicate a nonzero value $d'_{\text{Type I}}$ and paradoxically conscious perception. Therefore, in terms of the consciousness measure, establishing and maintaining appropriate decision-making are critical when detecting stimuli, rather than using sensitivity values $d'_{\text{Type I}}$ which rather would refer to the basic effectiveness of the information processing [42].

In terms of machine consciousness, it seems to be clear that the SDT approach by estimating sensitivity of first-order detection of emotion and bias can allow to determine computational correlates of social robot's objective knowledge about human affective states. A hypothetical robotic system (see **Figure 1**) with the functionality of objective consciousness of emotion may be equipped with emotion recognition algorithms that constantly analyze human expressions based on sequences of affective stimuli within time events and will then result in online SDT computations that simulate objective consciousness about recognized human affective state. In such a way, the use of the detection theory will enable to capture one of the key properties of conscious knowledge associated with choice behavior [44] in a possible robotic system.

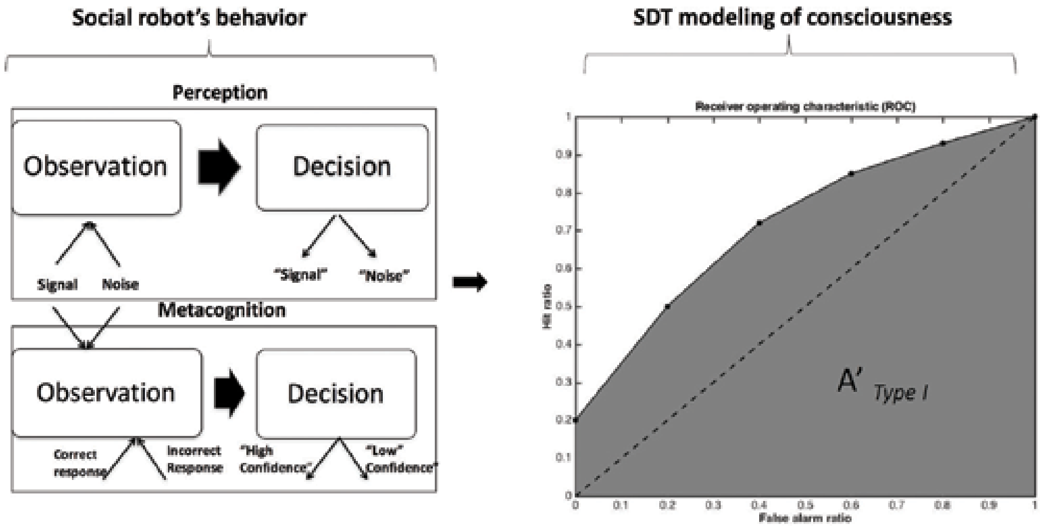

Figure 1. General idea of robotic system with measurement function of objective conscious perception of human emotions (inspired by [35]).

7. Signal-detection approach to encode metacognitive consciousness of emotion in a social robot

Objective theories of consciousness link consciousness to the ability of detecting incoming external stimuli by choice [45]. According to this view, consciousness is described as sensory processing that ignores first-person experience underlying subjective knowledge (metacognition) of its own representation of processing the incoming information. The problem of consciousness and its relations to metacognition has been viewed a central topic in consciousness research [46] which fits well the HOT approach [47]. This theory of consciousness is now considered to be a main framework that explains how people are aware of their conscious states [47]. On the one hand, HOT implies an assumption that consciousness depends on the presence of metacognition [48, 49]; on the other hand, there are opposite claims that metacognition is a prerequisite for the emergence of consciousness [50, 51]. According to this second assumption, consciousness is a first-person metarepresentation which refers to the ability to acquire knowledge about first-order mental states [52]. This second HOT view is well documented by studies on conscious learning with a neuronal network approach in which the brain via learning processes the information about external world and creates its own re-representation on how it is to be in a conscious state of the processed information [53, 54]. In fact, both the HOT theory and connectionist model are consistent with the signal-detection framework (see [53]).

Following the HOT view on consciousness, our conceptual framework assumes that a computational correlate of consciousness is relational property between first-order representation of emotion and metacognition [25]. Adopting such architecture of the machine consciousness indicates that metarepresentation is distinct from first-order representation and may require separate neuronal structures in the brain. In fact, brain research provides empirical evidence for feasibility of such architecture of neurocomputations showing that metarepresentation may be associated with activation of prefrontal and parietal regions [36], while low-level representation may be responsible for fast emotion recognition which depends on the amygdala [17, 55]. There is also convincing evidence of independence between these two types of knowledge representations from behavioral measurements of dissociation between correctness of performance in perceptual tasks and metacognitive awareness of such performance [33, 55] as well as neuronal instances of such dissociations in the brain [17, 56]. Common-sense intuition of brain activity also supports such view claiming that conscious knowledge about the stimulus does not relate to physical qualities of the perceived stimulus, but considers internal representations of the stimulus, which in turn refer to specific brain activation associated with stimulus perception [53]. It is worth mentioning that metacognition as higher level cognition, including monitoring, control processes, and evaluation, is sequential by nature [18]. Several computer modeling studies, for example, post-decision wagering procedures [57], demonstrate that metacognitive sequential strategies lead to consciousness of a stimulus. In the same vein, our brain study on metacognition with event-related potentials (ERPs) showed that metacognitive knowledge is crucial for conscious processing of emotion [58]. Similarly, a masking study with neural network simulations [54] shows that metacognitive knowledge can be underlined by a specific computational base for making conscious and unconscious decisions in terms of emotion detection. Unquestionably, empirical studies on consciousness and metacognition linked to the problem of accuracy of metacognitive knowledge, and its neurobiological and computational basis suggests that HOT is a theory that can be empirically verified.

Here, it is important to indicate that Szczepanowski [33] has shown that the relation between consciousness and emotion predicted by HOT can be modeled numerically with a signal-detection theory. In particular, SDT modeling has shown that under the emotion detection condition, subjective experience that expresses subjective feelings that accompany the first-order representation of affective stimuli can be embraced in the model by including participant's confidence responses [33, 55]. With regard to such SDT and HOT views, metacognition about task performance can be measured with a secondary sensitivity parameter $d'_{\text{Type II}}$ (see **Figure 2**). Evaluation of metacognition can include also $c_{\text{Type II}}$ parameter which is a second-order bias that identifies metacognitive strategies leading either to under- or overconfidence in task performance evaluations [46]. In this way, the second-order SDT measurements of consciousness provide objective information on subjective feelings of perceived affective stimuli.

In fact, Szczepanowski [33] has demonstrated that the SDT model of consciousness can embrace a hierarchical organization of affective processing, that is, objective information of performance in the emotion detection task must be reflected in a hierarchically higher level of processing. In this computational model of consciousness, there is an objective sensitivity measure of the perceived affective information (e.g., parametric first-order sensitivity $d'_{\text{Type I}} > 0$ or nonparametric $A'_{\text{Type I}} > 0.5$) as well as an objective measure of metacognition (e.g., parametric second-order sensitivity $d'_{\text{Type II}} > 0$ or nonparametric $A'_{\text{Type II}} > .5$ indices). The validity of this hierarchical SDT model was empirically proved with visual masking experiments with emotional faces (e.g., [35, 57]). In fact, the modeling outcomes based on SDT show that human consciousness with accompanying

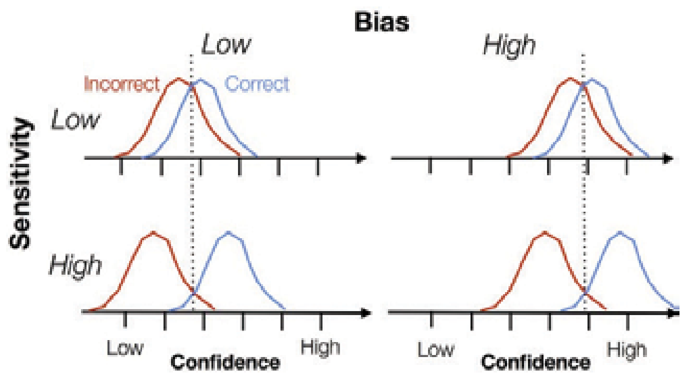

Figure 2. Measurements of consciousness and metacognition with second-order sensitivity and bias parameters based on SDT (source: [46]).

cognitive processes during detection of affective states may be a subject of empirical research. In addition, the interaction between consciousness and emotion can be related to decision-making processes which may be a result of computational-cognitive processes in the brain [33] and therefore potentially implemented into artificial environments of the social robot.

The above premises suggest that the hierarchical SDT model of consciousness can be used to determine computational correlates of robot's consciousness and its subjective experience of emotion. According to such SDT view, subjective conscious feelings of the robot may be related to execution of second-order operations on internally generated information from previous processing linked with detection of incoming stimuli from environment registered by a sensory system of the robot. We therefore assume that such conceptualization of machine consciousness within the robot is necessary to effectively regulate robot's behavior in terms of participation of metacognition in executing conscious control of cognition, in response to emerging affective information [18, 59].

8. Threshold approach to establish access consciousness for encoding C-E interaction by social robot

The third research domain for encoding C-E interactions by a social robot is to determine a computational correlate of global processing mode for consciousness of emotion. We assume that an adequate implementation of global information processing of emotion in the robotic system can be enabled by a threshold theory [33, 37]. As many experimental studies have demonstrated, representation of affective information is preferred to be accessed to conscious processing [60, 61]. For instance, in the area of consciousness research, backward masking studies provide substantial evidence that visual awareness occurs in the "all-or-none" fashion [62]. In the context of the masking task, this indicates that during stimulus detection, there is some sudden stepping-like burst of activation due to an incoming stimulus to enable transition between nonconscious and conscious states [63]. Some researchers suggest that such specific activation occurs in the brain as a threshold needed to activate access consciousness (see, for instance,

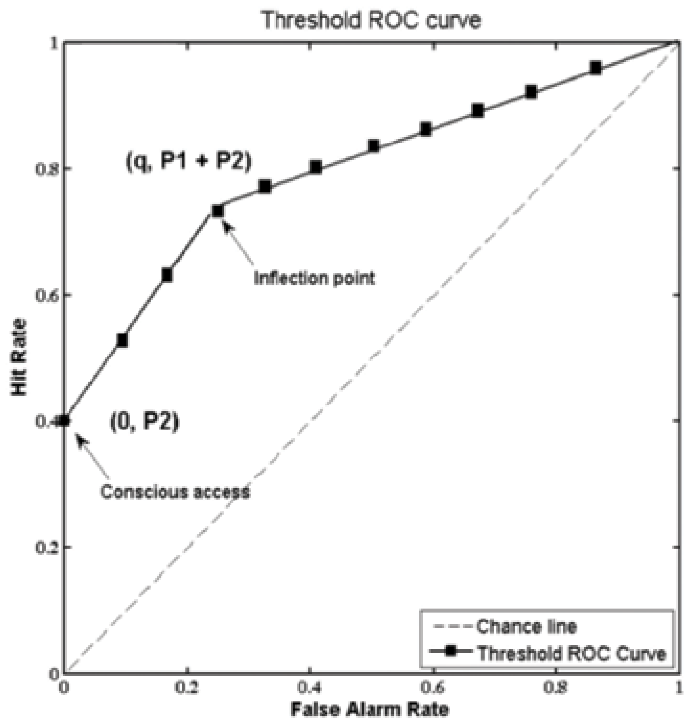

Figure 3. Linear ROC curve predicted by the Krantz's threshold model (source: [37]).

[63]). Indeed, Szczepanowski [33] has demonstrated that under a backward masking task, perception of fearful face happens in the "all-or-none" fashion and may be a factor explaining why this emotion information is preferable to conscious access. In particular, it appeared that in the visual masking experiments, several participants presented characteristic patterns of metacognition in terms of confidence in such a way that for the highest confidence, there are almost always hits without false alarms [37]. Because such observed response patterns followed ideal observer's behavior (hit responses without highest false alarms), the masking data have been successfully modeled with a Krantz's threshold detection theory [32, 33, 37]. This computational evidence that conscious perception of emotion is threshold-like processing implicates that under conditions in which stimulus strength is sufficiently large, the information content of the stimulus may be broadcasted in the system globally. This threshold-like information-processing approach to consciousness suggests that decision-making underlying emotion perception follows a discrete mental states' arrangement and its corresponding probabilities in terms of establishing conscious behavioral responses to affective information. Therefore, according to the outcomes from the threshold model, conscious processing in detecting emotion can activate global access to knowledge about emotion that manifests itself in ideal behavior of the observer.

The abovementioned outcomes suggest that global access to affective content in terms of metacognition (meta-knowledge) involves thresholds [33]. In other words, access consciousness may be activated for the highest confidence ratings on the "all-or-none" basis. In this way, conscious access to representation of emotions and metacognition can be quantified with signal parameters predicted in the Krantz model [32]. In the three-state threshold model (see

Figure 3), there are three mental states associated with perception, that is, the absence of ~D detection, D detection, and D* superdetection, and two thresholds, that is, upper and lower ones [32]. Detection of a target stimulus (probabilities P1 and P2) leads to mental states of D and D * (detection and superdetection), while detection of stimulus noise, described by the probability q, leads to a lack of detection ~D. The decision space described in the threshold detection theory is rectangular, and the ROC curve is linear as shown in [33]. It was demonstrated that participant who can consciously access to the stimulus content produces ideal observer behavior that can be estimated the P2 parameter [33]. Hence, the threshold model can predict situations in which the highest confidence is generated when there is conscious access to emotion content. Indeed, computational evidence for the threshold-like processing is an important discovery, since, so far, another view on perception has dominated in experimental psychology claiming that perception is continuous and should be described primarily by the Gaussian distribution [31]. Thus, in our conceptual framework of machine consciousness, we assume that conscious detection of emotion by the social robot engages global processing mode in the "all-or-none" fashion, and we propose to model these C-E interactions with the use of an innovative computational approach based on the Krantz's threshold theory [32].

9. Conclusions

As opposed to a typical application of industrial robots, a social robot needs to be considered as a social being with whom humans should be cooperating given a specific task structure. Therefore, the basic research aims of social robotics should be to determine computational models of the consciousness-emotion interaction designed to be implemented into a robotic platform. The request of preciseness in the context of computational models of emotions requires more research including related areas such as models of C-E interactions. This is a new research area in social robotics, and therefore it is potentially attractive from the perspective of development of computational models of emotion that are suitable for implementation in robots and contribute a new quality to the behavior of robots. It is believed that extending social robot competences and functionalities of HRI with C-E interactions will result in increasing acceptability of the social robot by the end user.

It seems that the abovementioned modeling outcomes of the C-E interaction based on the signal and threshold approaches are original contributions not only in the field of cognitive psychology but are crucial in the area of social robotics in terms of the possibility to implement high-level cognition into a social robot that effectively processes HRI in social domain [3, 4, 41, 64, 65]. In our conceptual framework, consciousness of emotion is the ability to detect affective information in the forced-choice condition, regardless choice decisions are low-level representation (features of the stimulus) or metarepresentation (subjective knowledge). In this way, consciousness may be attributed to an extremely simple function that can be associated with detection of different types of signals in the mind [33] and simply implemented into a social robot's design. In fact, adoption of the computational approach to consciousness that are based on quantitative detection parameters indicates that consciousness along with its subjective aspect is a specific function of the human brain and can be implemented into an artificial social robot's construction.

We believe that simplicity of such signal and threshold detection approaches that allow studying consciousness and its accompanying perceptual and metacognitive processes with the quantitative analysis will be optimal for implementing the C-E interactions into a social robot's system. Our successful attempts to operationalize desirable C-E interactions in the social robot within the signal-detection and threshold frameworks may provide valuable guidelines for implementation formal characteristics of conscious behavior into a social robot's construction and subsequently will be generalized for a much broader area of HRI. Finally, our understanding of cognitive mechanisms underlying consciousness and its subjective aspects will be the input to advance cognitive sciences, including philosophy of mind. In this way, our project will build a cross-disciplinary approach in designing effective HRI and machine consciousness that combine cognitive sciences and social robotics.

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Conflict of interest

Remigiusz Szczepanowski declares that he has no conflict of interest. Małgorzata Gakis declares that she has no conflict of interest. Krzysztof Arent declares that he has no conflict of interest. Janusz Sobecki declares that he has no conflict of interest.

Author details

Remigiusz Szczepanowski[1]*, Małgorzata Gakis[2], Krzysztof Arent[3] and Janusz Sobecki[4]

*Address all correspondence to: rszczepanowski@uz.zgora.pl

1 Institute of Psychology, Faculty of Education, Psychology and Sociology, University of Zielona Góra, Zielona Góra, Poland

2 Faculty of Psychology in Wroclaw, SWPS University of Social Sciences and Humanities, Wroclaw, Poland

3 Department of Cybernetics and Robotics, Electronics Faculty, Wroclaw University of Science and Technology, Wroclaw, Poland

4 Department of Computer Science, Faculty of Computer Science and Management, Wroclaw University of Science and Technology, Wrocław, Poland

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