Journal of Sports Research
2022 Vol. 9, No. 1, pp. 10-25.
ISSN(e): 2410-6534
ISSN(p): 2413-8436
DOI: 10.18488/90.v9i1.2897

ELECTROPHYSIOLOGICAL BIOMARKERS FOR THE ASSESSMENT OF MOTOR EFFICIENCY IN SPORT

Leonardo Ariel Cano[1,3,4+]
Alvaro Gabriel Pizá[2,3,4]
Fernando Daniel Farfán[2,3,4]

[1]*National University of Tucuman, Faculty of Physical Education, Department of Anatomy, San Miguel de Tucumán, Argentina.*
Email: lcano@herrera.unt.edu.ar Tel: +543815184483
[2]*National University of Tucuman, Faculty of Exact Sciences and Technology, Department of Bioengineering. San Miguel de Tucumán, Argentina.*
Email: gpiza@herrera.unt.edu.ar Tel: +543812122604
[3]*National Council of Scientific and Technical Research, Higher Institute of Biological Research, San Miguel de Tucumán, Argentina.*
Email: ffarfan@herrera.unt.edu.ar Tel: +543815785727
[4]*Laboratory of Neuroscience Research and Applied Technologies, San Miguel de Tucumán, Argentina.*

(+ Corresponding author)

ABSTRACT

Many disciplines have approached the study of human motor behavior. The motor learning theory based on information processing proposes a learning loop through interaction between the external environment and the central nervous system. Different neuroscience fields and technological advances provide a new perspective for the intensive study of the intrinsic processes of motor behavior, which modify the most visible aspect: motor efficiency. The aim of the present review was to determine which cortical and muscular electrophysiological biomarkers available in the literature could be representative for the study and quantification of motor efficiency. In this review, a survey of the literature related to motor production has been performed. The continuous development of biological signal monitoring techniques has allowed to understand part of the communication methods of the central nervous system, the integration of neural networks, and the interaction between different anatomic structures through rhythmic patterns of discharge known as brain waves. Motor production has been characterized by detecting electrophysiological biomarkers, taking into account the connectivity that can be represented by the corticomuscular and intermuscular coherence indices in different frequency bands. The present work proposes an approach to use these biomarkers on beta-band (for muscle stability synergies) and gamma-band (for mobility synergies). These indices will allow establishing quantitative parameters for motor efficiency, which could improve the precision of sports assessment.

Article History
Received: 22 November 2021
Revised: 24 December 2021
Accepted: 5 January 2022
Published: 14 January 2022

Keywords
Sport biomarkers
Motor efficiency
Motor control
Electroencephalography
Electromyography
Corticomuscular coherence
Brain waves
Muscular synergy.

Contribution/Originality: This study contributes to the existing literature related to motor control and motor efficiency and particularly focused on sports performance. This review addresses the electrophysiological basis of a proposal to quantify corticomuscular connectivity and muscle synergies, which offers great potential for developing methods based on physical-cognitive training.

1. INTRODUCTION

Many disciplines have tried to study human motor behavior, providing perspectives on biomechanics, physiology, psychology, neurocognitive, among others. In all these approaches, it is possible to find a common factor: the internal processes of the subject, each of them has focused on the variables that it can explain according to its criteria. In 1976, Marteniuk proposed a theory about motor learning based on information processing. This theory states that the subject receives stimuli from the environment in which the subject is into, makes a perception evaluating its possibilities of interacting with that environment, makes decisions based on its previous knowledge, plans and executes a motor response and evaluate the result instantaneously, triggering a new cycle of the same process Figure 1. This loop is the simplified mechanism of motor learning through interaction with the external environment. The central nervous system (CNS) is in charge of processing and managing all the information that the subject requires for the normal development of the motor interaction.

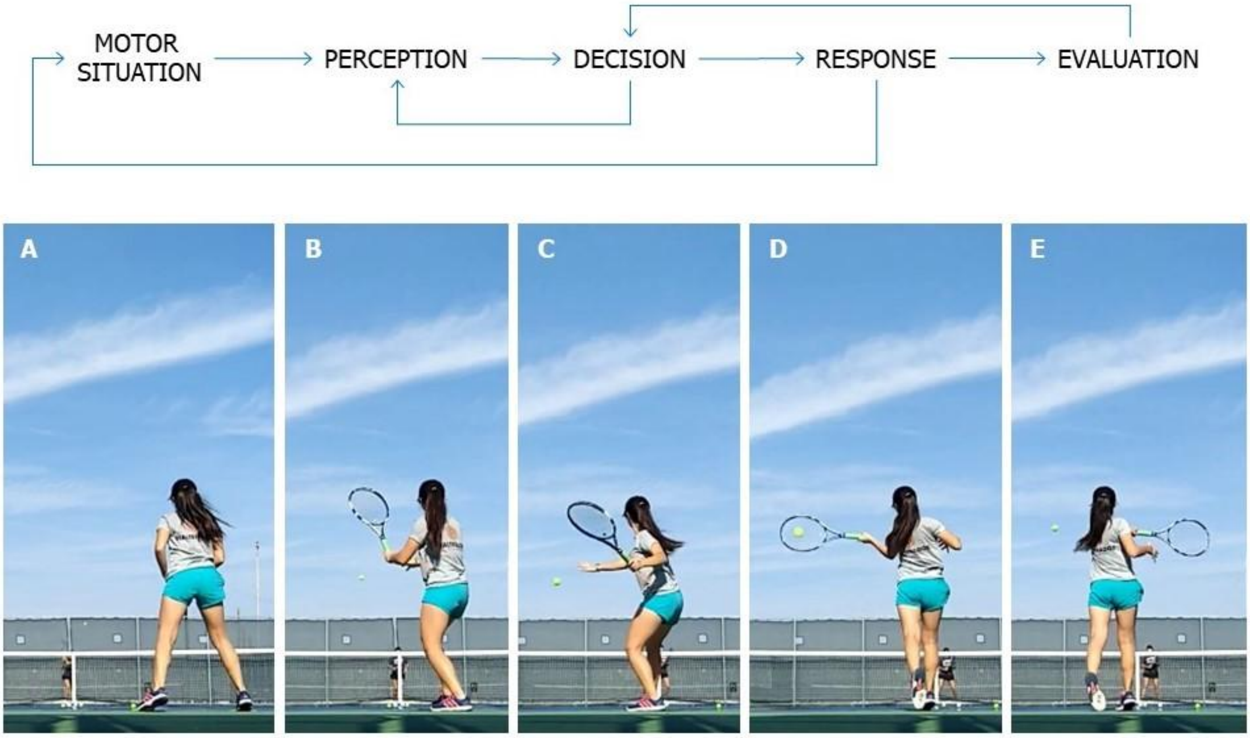

Figure 1. Loop model of motor learning theory adapted from Marteniuk (1976). (A) The player is in a motor situation that is a unique combination of the conditions of the entire environment, e.g., scoreboard, weather, audience, etc. (B) She perceives the space and time requirements before the preparation of the shot. (C) She analyzes the effectiveness possibilities for shot choice, then she programs the motor gesture. (D) She executes the movement by regulating the details that make it possible to resemble the previous planning with the subsequent motor execution. This execution places her in a new unique, and unrepeatable motor situation. (E) She evaluates the result of the perception-decision-response cycle procedure, which will have an impact on the next loops, generating learning by iteration.

The CNS organization has historically been studied in a compartmental and hierarchical way, dividing it into specialized structures for specific functions that allow for adaptive responses to the constant requirement of the organism. At the same time, it has interconnections that allow giving answers in situations that exceed the usual requirements. In this way, a specialized structure known as the cerebral cortex has been the object of study in some processes of motor behavior. This structure has special functions arranged in different anatomical regions that had paired with specifics functions organism known as Brodmann's areas (Brodmann & Gary, 2006). But at the same time, it has interconnections with other structures with which they integrate complex neural communication circuits. Two of the most studied areas of the cortex are the primary somatosensory (S1) and the primary motor (M1). The integration of these areas with other CNS structures is fundamental to the study of motor responses production. The neuroanatomical representation of these specialized areas was outlined by Penfield and Boldrey (1937) and is widely used in scientific research. However, the integration networks of cortical, subcortical, spinal areas and other determining structures in movement, like the thalamus, basal ganglia, and cerebellum (Kandel, Schwartz, & Jessell, 1996a) as well as the communication codes between them are not entirely clear.

In sports practices, different subject's sides intertwine when dealing with a motor situation. Somatosensory information is mixed, decisions are made based on motor skills, memory, emotional states; and finally, a response is programmed and executed. These components of the motor gesture have different effects on performance, modifying the most visible aspect: motor efficiency. The different fields of neuroscience and technological advance provide a new perspective for the intensive study of the intrinsic processes of behavior, allowing to elucidate the influence of these different sides during motor production, which will be closely linked to the quantification of sports performance. The aim of the present review was to determinate which are the cortical and muscular electrophysiological biomarkers available in the bibliography, which could be representative for the study and quantification of motor efficiency.

1.1. Monitoring Cortical Signals with Electroencephalography

Electroencephalography is a non-invasive technique that allows the study of electrical activity of the brain. Electroencephalographic recordings, known as electroencephalogram (EEG) signals, are captured through electrodes placed on the scalp. These signals are interpreted as the spatio-temporal sum of postsynaptic currents of hundreds of thousands of neurons that propagate through the biological tissue (connective tissue, skin, muscle) to recording electrodes. For EEG study and research, the International Federation of Clinical Neurophysiology provides guidelines and recommendations (Babiloni et al., 2020; Nuwer et al., 1998). EEG signal acquired continuously over time exhibits oscillatory characteristic in the range from 1 to 32 Hz in the clinical setting and up to 135 Hz in areas related to scientific research in neuroscience. That is mainly due to the connectivity characteristics between cortical neurons (inhibitory and excitatory). Frequently, EEG signals are obtained through multiple electrodes placed on the scalp, in specific and standardized positions according to the 10/20 system (Klem, Lüders, Jasper, & Elger, 1999) which allows establishing cortical topographic maps. The amplitude of EEG signals is in the order of a few to hundreds microvolts (µV), so it requires large amplification factors to be captured by the recording system. While high amplification factors (10,000 to 50,000 times, or 80 to 90 dB) raise these small signals to levels suitable for display and processing, they result in amplification of unwanted signal interference, such as noise artifacts, movement, network interference, electrocardiogram, electromyogram, and eye movement, among others. For this reason, numerous authors have reported certain disadvantages, drawbacks, and limitations of this monitoring technique (Cheron et al., 2016). However, it is still unsurpassed to date in terms of temporal resolution of the obtained cortical information, portability, non-invasive, and low-cost characteristics (Cohen, 2011).

1.2. Brain Communication through Neural Networks

The brain is in continuous activity, both in the moments of sleep and in wakefulness. Through EEG electrodes placed on the scalp is possible to look changes in electrical activity evoked by groups of neurons responding to specific sensory stimuli or neurocognitive processes. Thus, for example, in cortical areas of the occipital lobe, it is possible to look changes due to visual information entering through the eyes. While in the parietal lobe, it is possible to observe changes due to proprioceptive sensory input. In both cases, the cortical response is manifested through event-related potentials (ERPs). Cortical neurons communicate with each other through excitatory and inhibitory connections. Excitatory connections are characterized by favoring, facilitating, or contributing to the neuronal response, while inhibitory connections, on the contrary, depress the response capacity. In front of sensory or cognitive input, the response of the neuronal group is affected by both types of connection, causing an oscillatory response (Kandel, Schwartz, & Jessell, 1996b). When the neurons of a group, or several neuronal groups, are synchronized because they present similar discharge characteristics (without alterations or phase shifts). The energy of the activity observed from the EEG electrodes increase in the frequency of synchrony. Such an increase is known as event-related synchronization (ERS). On the contrary, when the EEG signal is affected negatively, its energy is diminished and refers to event-related desynchronization (ERD). The spatio-temporal analysis of both mechanisms provides information about the effective connectivity between the different cortical areas. In summary, the appearance of an ERP reflects the specific response of a group of neurons in the cortex given a stimulus that arrives via the afferent pathway, like from the thalamus, meanwhile ERS and ERD reflect changes in the continuous interaction between neuronal populations (Lopes, 1991; Pfurtscheller & Neuper, 2003).

Synchronization and desynchronization expose a complex and systemic method of communication between cells and neural networks. Through this selective activation, a neuronal cluster can prevent or allow the transmission of the action potential. About 85% of cortical neurons are excitatory, and the rest are inhibitory (Braitenberg & Schüz, 1998). In this context, the inhibition of neural networks is of utmost importance in the control of movement and the energy optimization, which is reflected in the synchronization of large networks during a time of idling (Klimesch et al., 1996). ERS/ERD is calculated based on the percentage increase/decrease of intensity concerning the baseline signal. A high ERS value at a certain frequency is associated with an inhibitory effect, while a higher ERD peak reflects the focus of the excitatory effect (Del Percio et al., 2010; Hwang, Ghuman, Manoach, Jones, & Luna, 2014; Pfurtscheller & Lopes, 1999). These effects are necessarily complementary. For example, to perform the movement of a body segment simultaneously, there must be network excitation in a certain cortical area and inhibition in another, this model was reported as "focal ERD/surround ERS" by Suffczynski, Kalitzin, Pfurtscheller, and Lopes (2001) and strengthened over time.

1.3. Brain Communication Methods

The most frequent analyzes applied to EEG signals are based on the determination of frequency characteristics (frequency spectrum) due to the oscillatory shape of them. From the statistical, EEG signals are considered non-stationary time series whose spectral content is in the range of 0.5 to 135 Hz (Babiloni et al., 2020). Singer (1993) showed that the oscillation frequency and the number of neurons involved in such activation could present an inversely proportional relationship. It is interesting to interpret this brain dynamic as the body's need to specialize neural networks and command them through a rhythmic pattern, that is, more specific functions for smaller networks (Penttonen, 2003). There is a consensus propose by the International Federation of Clinical Neurophysiology for the study of the different frequency bands classified according to an approximate range, known as brain waves Figure 2. Although the brain functions related to the processing of somatosensory information, emotions, memory, cognition and motor skills are still objects under study Muresan, Jurjut, Moca, Singer, and Nikolic (2008) it is important to note that each of these seems to have information differentiated in the various bands, a topic that we will approach on the next section.

1.4. Electrophysiological Biomarkers and Higher Brain Functions

Currently, there are discrepancies between the concepts of higher brain function (HBF) and higher mental functions (Tranel, Cooper, & Rodnitzky, 2003). However, both refer to the processes that differentiate the human brain from other species, particularly the ability to integrate neural networks in a complex way for self-analysis and future predictions. These functions are attention, learning and memory, language, consciousness, emotions, thinking, and reasoning. Probably the most relevant factor in the production of the motor response is decision-making, a process in which the HBFs integrate. This field of research is enormous, is in continuous development (Fellows, 2016) and there is large evidence to establish that HBFs process in specialized areas of the brain, both in the cortex and diencephalic structures, and that these regions integrate and interact continuously. The structures of the CNS seem to organize in different frequency bands for neural communication according to their role with the HBF, both at the cognitive and executive levels (Muresan et al., 2008). Next, we present some evidence of this organizational system.

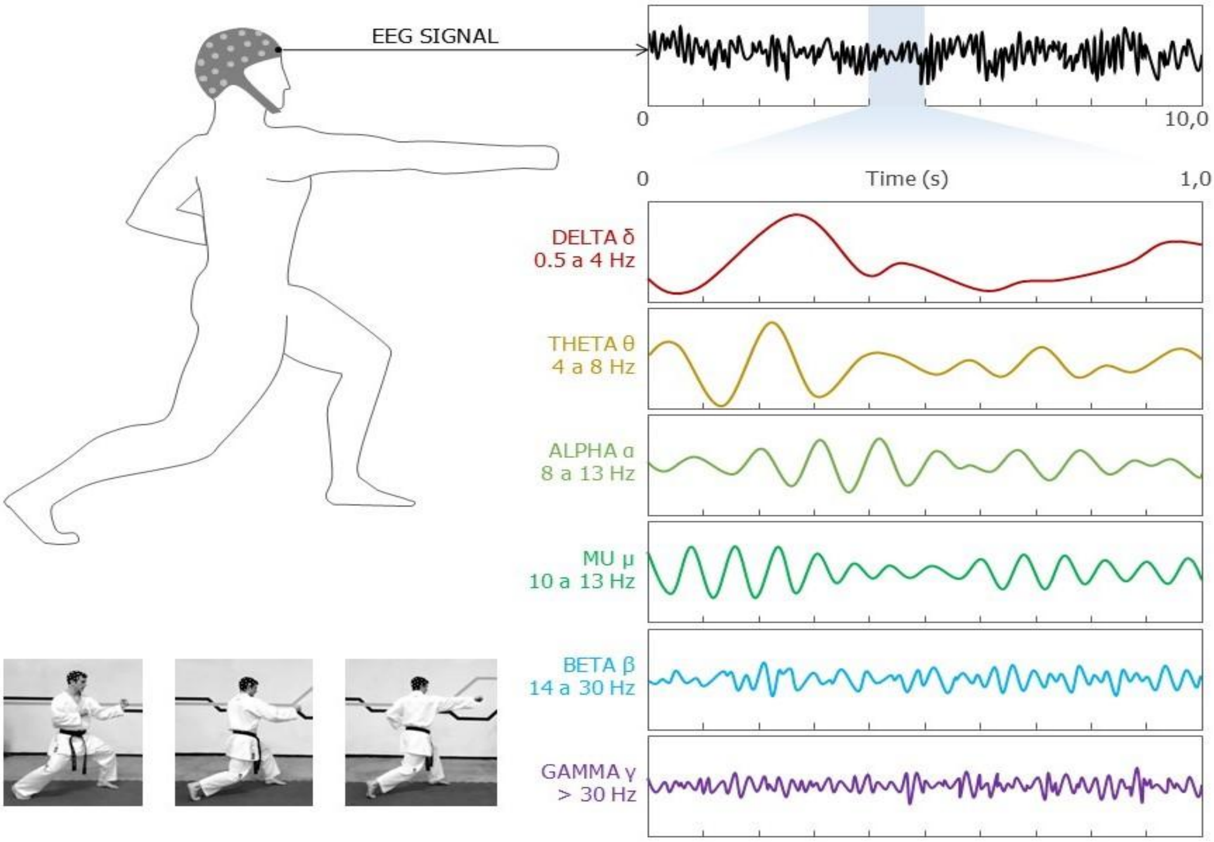

Figure 2. Brain waves classification. The frequency spectrum breakdown of a segment of the EEG signal captured by one electrode on one person's scalp is classified based on approximate oscillation ranges and named by letters of the Greek alphabet. The figure does not represent a real signal, only is for educational purposes.

The Figure 2 shows that low-frequency oscillations such as the delta wave (0.5 to 4 Hz) are related to the thalamic-cortical system (Steriade, McCormick, & Sejnowski, 1993). Theta wave (4 to 8 Hz) with hippocampus (Maurer & McNaughton, 2007). Both activities are observed during the sleep state, in the nREM and REM phases respectively, and they are related to neuronal plasticity, learning, and memory consolidation (De Gennaro et al., 2008; Tononi & Cirelli, 2014; Watson & Buzsáki, 2015). In the awake state, these waves appear coupled with high-frequency waves when brain functions require hierarchical organization (Canolty & Knight, 2010). For example, keeping working memory active using delta waves to activate selective attention or visual discrimination, this coupling is called "delta-gamma coupling" (Händel & Haarmeier, 2009; Lakatos, Karmos, Mehta, Ulbert, & Schroeder, 2008). To retrieve information of spatio-temporal parameters from episodic memory in the hippocampus and entorhinal cortex at the service of motor control is called "coupling theta-alpha and theta-beta" in S1 and M1 (Hasselmo & Stern, 2014; Ofori, Coombes, & Vaillancourt, 2015).

Brain rhythms around 10 Hz are called alpha waves and appear resting and specific actions of the sensorimotor system. However, recent research has described specializations in this band. The lowest (8 to 10 Hz) are associated with information from the visual cortex and thalamus (Saalmann & Kastner, 2009). While, the highest (10 to 13 Hz) are called mu, they are found in the pre and post-central area in the frontal and parietal lobes and are associated with processes in the somatosensory and motor cortex (Ai & Ro, 2014; Babiloni et al., 2008; Del Percio et al., 2010; Taliep & John, 2014) and even they appear in the movement imagination (Fink et al., 2018).

Waves between 14 and 30 Hz are known as beta waves. These oscillations play a role in the planning and control of movement by integrating different regions of the CNS: supplementary motor area (SMA), premotor (PM), primary motor (M1), primary somatosensory (S1), and cerebellum (CBL) (Courtemanche & Lamarre, 2005; Hosaka, Nakajima, Aihara, Yamaguchi, & Mushiake, 2016; Lebedev & Nelson, 1995; Lebedev & Wise, 2000; Reimer & Hatsopoulos, 2010). These investigations have been conducted in monkeys and through ERP records, but interaction mechanisms between these regions are still studied. Activity in this band is broad and involves specific synchronizations for motor control through cyclical processes of perception in which HBFs are involved, such as selective attention, sensory awareness, and working memory (Engel & Singer, 2001). Currently, the scientific evidence about the manifestation of beta waves in the activation mechanisms of the mirror neuron system, which intervenes in proprioceptive recognition before sensory information, is increasingly firm and has implications in planning and motor learning (Cebolla, Palmero-Soler, Dan, & Cheron, 2014). Also, beta waves are associated with Autonomous Nervous System (ANS) and sympathetic functions. For example, elevate the heart rate to prepare the organism before the execution of a motor response (Triggiani et al., 2016).

High-frequency waves are observed from 30 Hz and are called gamma. This activity (as occurs with beta waves) is localized, transitory, also related to HBF linked to motor tasks (Babiloni et al., 2016). There is plentiful information about the participation of this rhythmic pattern in the activation of motor areas and the corticospinal pathway, a topic that we will develop later. A particular characteristic of this frequency is that it has sufficient resolution for emotions recognition and differentiation (Li, Xu, Liu, & Lu, 2018; Yang et al., 2020) and allows recognizing the efferent location from the amygdala (Amir, Headley, Lee, Haufler, & Paré, 2018; Bocchio, Nabavi, & Capogna, 2017; Feng et al., 2019).

Despite the extensive literature information and continuous efforts trying to establish electrophysiological biomarkers (EFBMs) for explain the mechanisms of HBFs, the classic methods based on electroencephalographic changes (such as ERS and ERD) still are not very effective when studying more complex mechanisms such as reasoning or non-motor abstract imagination.

1.5. Interaction between EFBMs: Brain Dynamics for Motor Production

The study of motor production is one of the most interesting challenges in neuroscience, and for this purpose, the EEG provides information of high density and great temporal resolution. The hypothesis of Neural Efficiency (Grabner, Fink, Stipacek, Neuper, & Neubauer, 2004; Neubauer & Fink, 2003) has been propose closely related to the intelligence quotient (IQ) for monitoring spatio-temporal patterns of cortical dynamics before, during and after a motor action. This analysis is based on the decrease/increase of brain activity (ERD/ERS) in some frequency bands and its application has been demonstrated by classifying the sample according to the level of sporting expertise (Babiloni et al., 2008; Babiloni et al., 2010; Del Percio et al., 2010; Dunst et al., 2014; Grabner et al., 2004; Haegens, Osipova, Oostenveld, & Jensen, 2010; Klimesch, Sauseng, & Hanslmayr, 2007). This evidence allows us to think that the CNS is more efficient when it has more experience in motor gestures, so the motor production system would require fewer neural resources, that is, less neural effort.

The neural effort analysis, according to the hypothesis mentioned in the previous paragraph, shows the dynamics focused on a specific region. It established that this concept is more related to cognitive-motor performance than to the efficiency of the complete circuit, since motor production is linked to interaction with other brain structures in networks (Laughlin, 2003; Sporns, Tononi, & Kötter, 2005). In this line, the hypothesis of Psychomotor Efficiency (Rietschel et al., 2012) has been proposed based on the coherence analysis of the frequency components of electrical activity that is interpreted as "connectivity" between different brain regions. This concept involves the need for the CNS to resort to HBFs that occur in anatomically distant but connected structures, as we have already analyzed previously, to produce an effective response that meets the demand of the task. This hypothesis has been studied through the classification of the task according to the complexity and the demand for resources. The increase in task difficulty is directly proportional to neural effort (greater focused ERD in combination with greater non-focused ERS) and connectivity (greater coherence between the waves of different brain structures) (Gentili et al., 2018; Gevins & Smith, 2003; Shaw et al., 2019). For example, in a specific cognitive-motor task, such as the Tetris® game, a high level of difficulty reveals high levels of neural effort characterized by mu, theta and beta ERD, and gamma ERS, and increased connectivity between different regions of the CNS in these brain rhythms (Rietschel et al., 2012). It is interesting to interpret that the increase or decrease in connectivity between regions seems to establish an excitation/inhibition pattern in the neural networks involved, thus establishing spatio-temporal networks of brain activation (functional connectivity). Although this speculation is consistent with several observations, there is still no concrete evidence for its validation (Shaw et al., 2019). This idea seems to take logic from the analysis of neuronal interaction in which a single synaptic connection in the neuronal soma can inhibit all the excitatory action potentials received by that cell (Kandel et al., 1996b).

To date, there is ample evidence that EFBM explains some mechanisms in the motor production process. Is possible to speculate that they play a central role in the integration of different brain structures and, consequently, the integration of HBFs. However, so far it cannot be conclusively established.

1.6. Motor Production and Corticomuscular Integration Circuits

We have detailed so far that motor production depends on the integration of different regions of the CNS, such as the cortex, cerebellum, diencephalic structures and even the spinal cord. This integration is mediated by a complex neural communication system through a hierarchical order in the oscillatory rhythms. The result of these interactions is translated into the excitation of pyramidal neurons (PNs) in motor areas (Asanuma, Zarzecki, Jankowska, Hongo, & Marcus, 1979; Baker, Kilner, Pinches, & Lemon, 1999; Jackson, Gee, Baker, & Lemon, 2003; Keller, 1993; Lemon & van der Burg, 1979). There is evidence that the oscillations in the cortex observed in the EEG are related to the oscillations in the spinal cord (Baker, 2007; Van Wijk, Beek, & Daffertshofer, 2012). It demonstrates communication by more precise patterns through the corticospinal pathway, which determine muscle activation through motoneurons.

The dynamics between the oscillations recorded in M1 (PNs area) during the body segment movement have been studied in such a way that defined patterns are observed based on the requirements of the motor gesture. Sequential dynamics of ERD pre/during movement and ERS post-movement in mu and beta bands were observed. This phenomenon is understood as a focal somatotopic activation followed by a synchronization necessary for the basal level reestablishment (Pfurtscheller, Stancák, & Neuper, 1996; Pfurtscheller & Lopes, 1999). The strength and speed requirements seem to establish the characteristics of the activations, such as the anticipation time and intensity of the ERD before/during the movement, and the intensity and duration of the post-movement ERS (Stancák & Pfurtscheller, 1996; Stančák, Riml, & Pfurtscheller, 1997). In support of this idea, it has also been established that there is an increase in the intensity of post-movement ERS when the amount of muscle mass involved increases (Stančák, Feige, Lücking, & Kristeva-Feige, 2000). In cyclical gestures, higher movement speed tends to modulate lower ERD and ERS peaks (Toma et al., 2002). Muscle tone seems to be controlled with a functional level of ERS in beta, proving that an abrupt increase in intensity through transcranial magnetic stimulation prevents the efficient development of a motor gesture (Pogosyan, Gaynor, Eusebio, & Brown, 2009). In this way it has been established that a decrease in synchronization is necessary to favor the start of a movement. Also, there is evidence to think that the gamma ERS explains the activation of a precise muscular functional unit due to a very focused and very transient somatotopic activity is observed in the contralateral hemisphere, both at the beginning and at the end of the movement (Van Wijk et al., 2012).

The connectivity between M1 and the corticospinal pathway, as mentioned above, can be studied through the coherence analysis of the oscillatory activity. Thus, it is possible to observe an increase in corticospinal coherence (CSC) in the beta-band during the production of moderate isometric force (Androulidakis, Doyle, Gilbertson, & Brown, 2006; Chakarov et al., 2009; Witte, Patino, Andrykiewicz, Hepp-Reymond, & Kristeva, 2007). Similarly, in response to the demand for greater force production, an increase in CSC in the gamma-band was observed (Andrykiewicz et al., 2007) and increasing beta coherence in PM (Feige, Aertsen, & Kristeva-Feige, 2000) and SMA (Chen, Entakli, Bonnard, Berton, & De Graaf, 2013) regions. This dynamic allows action potentials to be triggered in the motor units (MUAPs) that will cause the subsequent contraction of the muscle fibers (De Luca & Forrest, 1973).

Communication between M1 and muscle is a topic that has been under study for a relatively short time (Baker, Olivier, & Lemon, 1997; Conway et al., 1995) and there are many controversies in the interpretation of EEG and EMG signals (Farina, Merletti, & Enoka, 2004, 2014). Corticomuscular coherence (CMC) is an index used to establish connectivity between cortex regions and muscle activation through the frequency spectrum correlation of both signals (Fang et al., 2009). Although CMC can occur in both directions of information flow (from cortex to muscle, or from muscle to cortex). But, it is rather accepted that CMC occurs in a downward direction in the corticospinal pathway (Liu, Sheng, & Liu, 2019) because of this reason, the delay inherent in the electrophysiological processes of the signal transmission must be taken into account (Xu, McClelland, Cvetković, & Mills, 2016). The communication mechanism between the motor cortex and the muscle is a field that continues to be highly studied.

Current observations support the hypothesis of the existence of differentiation between static force production strategies (with beta-band CMC) and dynamic force production (gamma-band CMC) (Gwin & Ferris, 2012; Reyes, Laine, Kutch, & Valero-Cuevas, 2017). This functional differentiation seems to be related to the characteristics of the recruitment and motor units firing frequency as a function of the task (Conwit et al., 1999; Van Wijk et al., 2012). There are functional aspects that fortify the postulates of CMC as an efficiency parameter in motor production based on modulation of connectivity like strength requirements, age, and neuromuscular pathologies (Liu et al., 2019).

The mechanisms underlying the organization of muscle coordination are intervened by cortical signals, but also by neuromuscular interconnections at the spinal level (e.g. reflex inhibitions). This level of communication is studied through an intermuscular coherence index (IMC), which has gained great relevance in recent years and allows to explain the mechanisms of co-activation and synergy in muscle networks (Boonstra et al., 2015). Even though IMC seems to be an effective indicator when it comes to characterizing the muscular functional aspects in a motor task, scientific advances in this line should likely consider the origin of the signals involved (Frère, 2017; Ranganathan & Krishnan, 2012).

For all the above, it is possible to postulate that there are muscular synergies in motor production. On the one side, to stabilize joints that would occur through tonic muscle contractions controlled by neural stimulation in the beta-band. And on the other side, phasic muscle contractions constituted by agonist/antagonist muscle networks communicated controlled by gamma-band with a wide range of high-frequency oscillations, which would allow modulating the strength expression.

2. DISCUSSION

This review reveals a great methodological divergence when studying aspects of motor production. It is logical to think that this great variety of conditions is due to the stage of maturity in which this topic is now. The diversity of designs, the use of emerging technologies for measurement, the variety of techniques for information processing, and the lack of consensus on observed variables, still do not allow to generate conclusions for the sports field. For this reason, to monitor and quantify motor production, and then determine the efficiency of the system, we consider that is necessary to establish external conditions that are more related to sport interest characterizing the difficulty of the task based on space-time requirements for motor production as an independent variable.

Figure 3 shows an expanded version of Figure 1 to which we have integrated the aspects that have been developed throughout this review, which are components that we recommend taking into account in the analysis of a motor gesture.

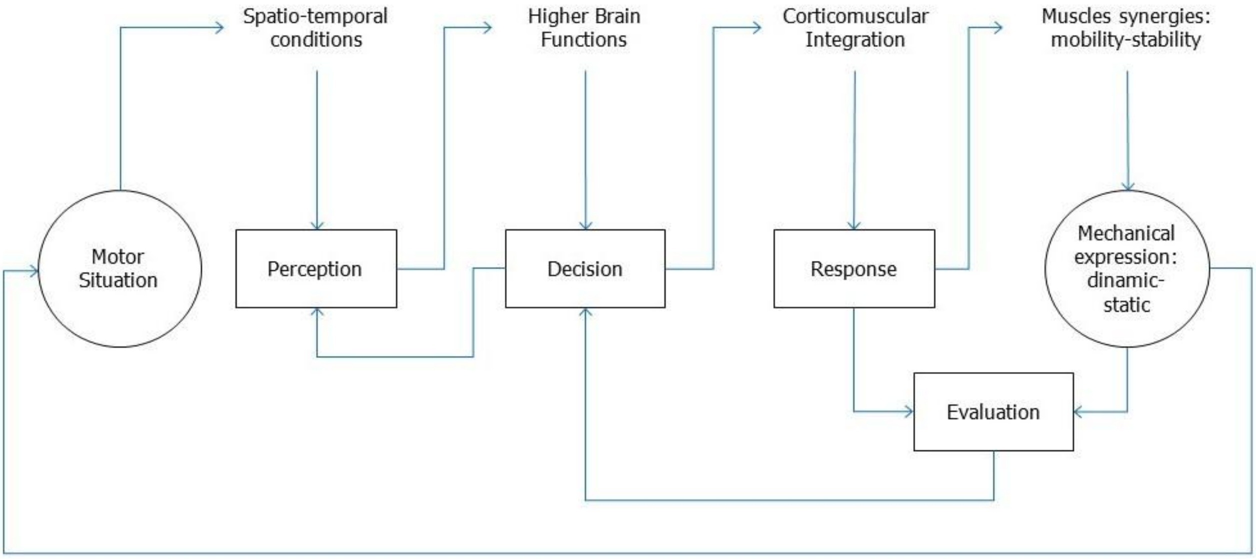

Figure 3. Process diagram in the motor gesture development, the influence of context and feedback for learning and optimization of motor production.

In this work, we have differentiated two stages on motor production (Figure 4): planning and execution according to a model adapted by Kandel et al. (1996a) but originally proposed by Allen and Tsukahara (1974). In the first instance, motor planning implies the connectivity of the different CNS regions to provide an effective response that meets the demands of the motor situation. This connectivity involves the integration of various HBFs such as attention, memory, and/or emotions. The final decision on the response to executing is manifested in M1. In a second instance, information is simultaneously emitted from M1 to the different motor units through the corticospinal pathway. The performance will be the combination of excitation and inhibition signals that have reached the muscles involved in the planning phase. In this combination, the recruitment patterns are ordered and coded to achieve a coordinated motor gesture with differentiated muscular activity for stabilization (stability synergies) and mobilization (mobility synergies) of body segments. Therefore, the differences between motor production strategies could be explained through corticomuscular connectivity.

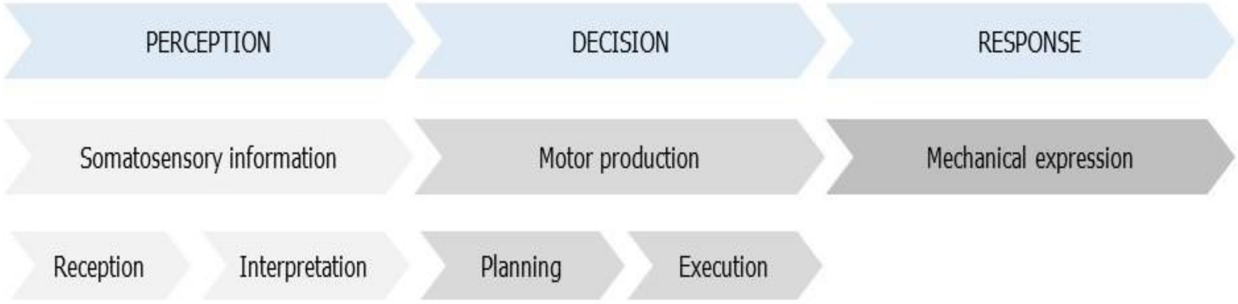

Figure 4. Sequential model for the motor gesture study combining motor learning theory based on information processing (Marteniuk, 1976) and motor production stages (Kandel et al., 1996a) in which motor production is considered to correspond to the decision phase. In temporal terms, the decision begins after the perception ends. This mean that the decision phase starts when the information of the motor situation and the context has already been interpreted, and ends when a mechanical expression is registered (force application, movement, tissue deformation, or others).

Based on the evidence presented for EFBMs used to assess motor production (Baker et al., 1997; Boonstra, 2013; Conway et al., 1995; Gwin & Ferris, 2012; Liu et al., 2019; Reyes et al., 2017) we propose that beta-band CMC could explain stability synergies, and the gamma-band CMC could explain mobility synergies. In this sense, it is possible to assume that a higher beta CMC would explain a greater effort by the CNS to establish the stability of the segments necessary to provide biomechanical solidity to the structures involved, which is a fundamental aspect that will precede effective execution. This greater CNS commitment may be inversely proportional to the system efficiency, in the sense that a higher IMC with a common neural origin could be considered as a coordination strategy with a greater degree of automation and efficiency. Similarly, a higher gamma CMC could explain the involvement of M1 in muscle activity, in such a way that the higher the connectivity value, the greater the effort of the CNS, provided that the motor task has been fulfilled. To graphically express the hypothesis proposed in this discussion, we have represented a connectivity scheme in Figure 5.

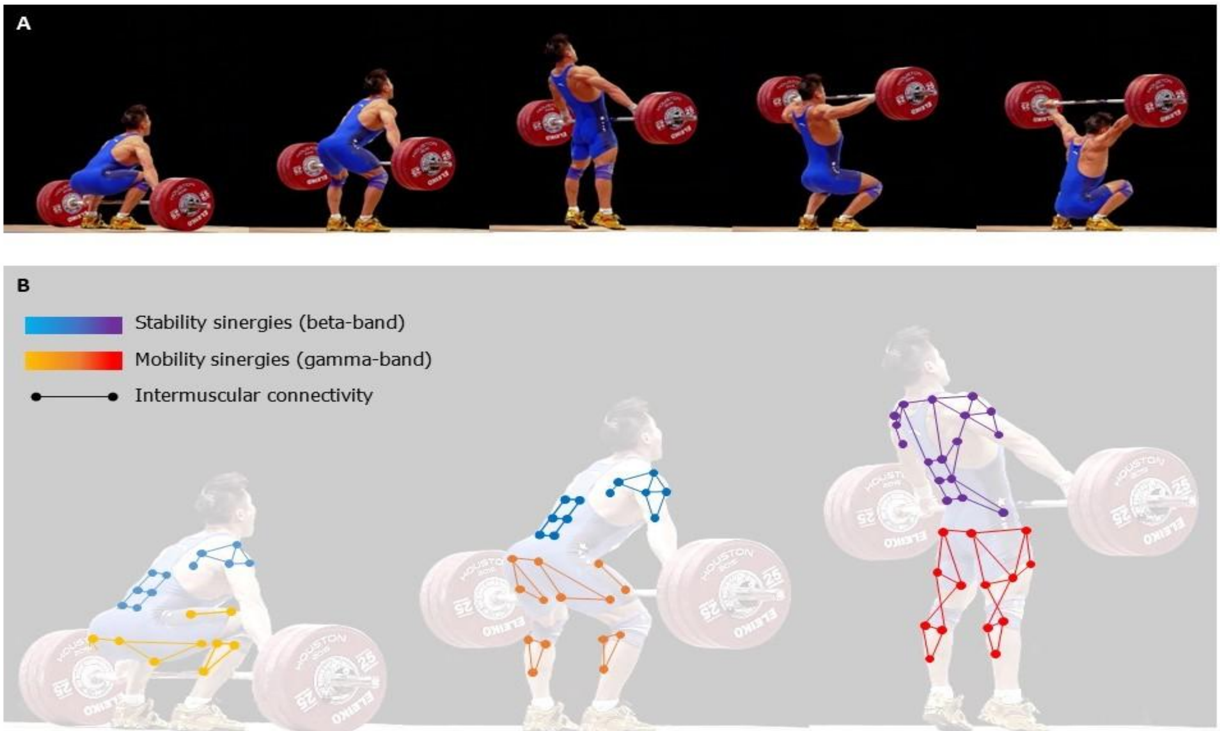

Figure 5. Representation of corticomuscular and intermuscular connectivity in a sports movement. (A) A sequence of weightlifting movements in competition. (B) A fictitious representation of stability and mobility synergies in color scales for involved muscle networks. The blue and yellow colors represent a lower CNS involvement, while the purple and red colors represent a maximum CNS involvement quantified through the CMC (connectivity between M1 and muscles). The circles represent the muscle sensors, while the lines between them (intermuscular connectivity) are defined according to the IMC.

3. CONCLUSION

In this review, we have examined how is the participation of different brain waves in motor production and their expression in muscle activity. We understand that there is sufficient evidence to consider the scientific potential of calculating CMC and IMC in the beta and gamma bands (and their interactions) for the EFBMs development to establish quantitative parameters of motor efficiency. Additionally, we recommend that research about the motor situation should be designed according to the difficulty of the motor task, which must be related to the space-temporal requirements of the context of each sport and/or motor gesture of interest.

Funding: The National Council of Scientific and Technical Research (Argentine Republic) funded the research by grant project (RESOL-1225-APN-DIR#CONICET).
Competing Interests: The authors declare that they have no competing interests.
Acknowledgement: All authors contributed equally to the conception and design of the study.

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