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Triggers of motor activity measurable by near-infrared functional spectroscopy (fNIRS): a review

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Abstract. Scientific studies have differed on the interpretation of activity in the primary motor cortex of the brain. Various studies have found that the primary motor cortex is activated only during physical motor tasks. Whereas other studies have appeared that a similar measurable activity can be observed and recorded when arousing or stimulating the motor cortex when performing a mental representation of movement. Consequently, our purpose of this review was to compare the triggers of motor cortex activation during the physical execution and mental representation of the movement by recording the brain signals resulting from the stimulation by using the technique of near-infrared functional spectroscopy based on the neural interface (brain-computer interface). This research reveals differences and comparisons based on various approaches to analyze and systematically realize target triggers of motor cortex activation during training at neural interface (fNIRS). Based on the above, this review concludes by emphasising the fact that triggers of cortical activation in general and under different names cause activity that can be recorded by measuring the various changes that occur in hamoglobin concentration, in other words, that both physical task performance and similar mental representations of movement cause perceptible activity in the motor cortex. This provides the rationale for prosthetic, rehabilitation and other applications. Furthermore, this encourages future research to identify positive triggers for cortical activation to study psychological states of cognitive function and certain pathological conditions, as well as neurophysiological studies.

Keywords: near-infrared functional spectroscopy, triggers, motor cortex, brain-computer interface, physical movement, mental representation of movement.

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Триггеры двигательной активности, измеряемые с помощью функциональной спектроскопии в околоинфракрасном диапазоне (fNIRS): обзор

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Резюме. Научные исследования разошлись в интерпретации активности первичной моторной коры головного мозга. Различные исследования показали, что первичная моторная кора активируется только во время физических двигательных задач. В то время как другие исследования показали, что аналогичную измеримую активность можно наблюдать и записывать, когда моторная кора возбуждается или стимулируется во время мысленного представления движения. Таким образом, целью данного обзора было сравнение триггеров активации моторной коры во время физического выполнения и мысленного представления движения путем регистрации сигналов мозга, возникающих в результате стимуляции, с использованием метода функциональной спектроскопии ближнего инфракрасного диапазона на основе нейронного интерфейса (интерфейс мозг-компьютер). Данное исследование выявляет характерные черты и сравнения на основе различных подходов к анализу и систематической реализации целевых триггеров активации моторной коры во время обучения на нейронном интерфейсе (fNIRS). Основываясь на вышеизложенном, в заключение данного обзора подчеркивается, что триггеры активации коры головного мозга в целом и под разными названиями вызывают активность, которая может быть зарегистрирована путем измерения различных изменений, происходящих в концентрации гемоглобина. Иными словами, как выполнение физических задач, так и сходные ментальные представления движения вызывают ощутимую активность в моторной коре. Это предоставляет обоснование для протезирования, реабилитации и других применений. Кроме того, это стимулирует будущие исследования по выявлению положительных триггеров активации коры для изучения психологических состояний когнитивных функций и определенных патологических состояний, а также нейрофизиологических исследований.

Ключевые слова: функциональная спектроскопия ближнего инфракрасного диапазона, триггеры, моторная кора, интерфейс мозг-компьютер, физическое движение, мысленное представление движения.

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Introduction

In biological philosophy, despite the fact that all the organs of the human body are important and deserve to be taken care of, studied and monitored for their continued health, the brain is the most complex organ and distinguished from the rest of the organs as the main motor and the center of nervous communication. Artificial intelligence with its tools known as neural networks that have dominated medical technology, which can be said to be computer biological models that explain internal physiological reactions to the visual world, and limited to the brain mechanism, neural networks detect recordings of brain signals and translates them into actual commands. The human brain is divided into two folds , one dominant and the other non-dominan and is controlled by extensive neural networks between interconnected cortical areas. Strenuously interconnected neural networks may be the control tool of human motor and sensory functions as well, cortical and even non-cortical structures of each neural network may be involved in the recording and processing of various information related to brain functions.

Brain-computer interface (BCI) or neural interface is an integrated interaction system (hardware and software) functionally based on real-time detection of characteristic signals (patterns) of brain activity using neuroimaging techniques such as fNIRS, and on conversion of the received information into control commands for external devices such as prosthetics, wheelchair and others [1, 2].

Neuroimaging is a new neurophysiological paradigm for studying brain activity. Neuroimaging in medicine is useful for detecting brain tissue damage, diagnosing skull fractures, and brain injuries. Today, it is increasingly used to diagnose behavioural and cognitive diseases (e.g. age-related neurodegenerative changes), metabolic disorders and small lesions (e.g. epileptic foci) [3]. In addition, functional neuroimaging capable of creating a BCI that is interested in analyzing and studying the tasks generated by the central nervous system (CNS) as the dynamics of cerebral work, the working dynamics of the brain, the movement of blood in the vessels, as well as changes metabolic activity. The most well-known neuroimaging techniques for studying the activity of the motor cortex (MC) are functional magnetic resonance imaging (fMRI) and fNIRS method. fMRI has previously been widely used as a means of studying functional brain activity, but due to its large size and conditional limitations on subject movement, it is difficult or impossible to assess brain function during exercise using this method. Brain imaging techniques fall into two modalities: invasive, which require surgical intervention, and noninvasive, which does not require surgical intervention.

The fNIRS technique is one of the noninvasive techniques characterised by important features such as reliability, portability, no radiation, and ease of installation and use (Figure 1), making it one of the most popular technologies in today's scientific and experimental research circles.

Figure 1 – Shows how simple the fNIRS technique works. The girl in the photo is conducting an fNIRS experiment as part for researching and developing of a prosthetic control system in the laboratories of (BSU) in Russia
Рисунок 1 – Показывает, как просто работает методика fNIRS. Девушка на фото проводит эксперимент fNIRS в рамках исследования и разработки системы управления протезами в лабораториях (БелГУ) в России

Despite the advantages of fNIRS, it is not without disadvantages such as low spatial and temporal resolution. However, when fNIRS forms a combined system with magnetic brain planning technology, the system will be characterized by high spatial and temporal accuracy, and this may be a solution that overcomes the disadvantage of this technology [4].

Another disadvantages of this technique is the delayed haemodynamic response; however there are also recent studies aimed at rethinking the delayed haemodynamic response, suggesting that this technique is still the focus of current research [5]. It is widely believed that primary MC activity is associated only with movement execution. However, the extent to which such activity is involved in imagining movements has yet to be identified. While some investigators have reported primary MC activity during both motor performance and movement imagination tasks, others have reported no effects on movement imagination. It remains unknown whether the patterns of brain activation during movement performance and movement imagination or whether both tasks activate the primary MC are similar.

Furthermore, the effect of imagination intensity on the primary MC is unclear although it has been well studied in motor tasks [6]. Similar to the above, this review has taken on the task of examining the triggers of MC activation and comparing them regarding performing a physical movement and mentally imagining a similar movement, benefiting from the output of of practical experiments that have touched on the essence of this topic.

Scope of research methodology and materials

The scope of the research methodology varied from the use of several databases, articles in different languages and books, all of which are indexed on documented sites and are relevant to the research. The comprehensive scope of the research highlighted the outputs and studies of the last decade using using the keywords "fNIRS" or its constituent words and "BCI" or its constituent words, motor and imagery performance.

The research methodology also included materials that would cause stimulation of the MC such as hand movement, as well as materials of a biological nature such as verbal fluency and other materials that would stimulate the MC. Numerous articles were excluded and others were ignored, as both did not fit into the concept of the topic, and the citation of relevant and useful articles that contribute to making the article a clear value and benefit for those interested in scenarios of medical neuroimaging technologies in various clinical applications. Thus from hundreds of scientific articles interested in the research topic, 66 authoritative scientific articles were filtered and identified in this study. The most important parts of the research methodology that a researcher can use are https://scholar.google.com/, elibrary.ru, https://www.mdpi.com/journal/sensors, https://www.refseek.com, https://link.springer.com/, https://www.base-search.net and others.

Activation of the MC as a target for fNIRS-based BCI

The results of intensive research in neuroscience and neurotechnology have made it possible not only to predict human sentimental and cognitive states, but also to manage interactions between different people. The great advantage of BCI, which is based on recording brain activity, is the quick transfer of information from the brain to an external device. In fact, the main purpose of active and passive BCIs is to interpret the user's intentions by monitoring brain activity. Brain signals include many individual events related to an intentional cognitive or motor task. Although most of these events are difficult to explain physiologically and their origin is unknown. However brain activity signals corresponding to these events can be decoded and interpreted by BCIs [7–9], or through a hybrid BCI system [10], to generate commands appropriate to an external device or to the operators themselves.

The first step in the development of fNIRS-based BCI is to acquire relevant brain signals. The fNIRS technique records signals of a visual nature. BCIs work for all areas of the brain depending on the condition to be evaluated, but the most common areas are the primary MC and the prefrontal cortex [11, 12], which is of interest in the study of BCIs. Seung Y. B et al. found that patients with major depressive disorder have relatively reduced levels of oxyhemoglobin in the left frontal lobe during a verbal fluency task, suggesting frontal lobe asymmetry in the relationship between severity of depression and suicidal ideation [13]. Fubiao Huang et al. found that during a task with additional targets, there is greater activation of the prefrontal cortex than that during a single target task. This means that additional goals further activate the prefrontal cortex, and this provides occupational therapists with effective guidelines for therapeutic practice [14].

Although different source-detector configurations are used in different fields, the source– detector spacing is usually kept within a certain range this is due to measurements are of great importance in measurable biological detection. A distance of approximately 3 cm has been proposed for measuring circulatory response signals from cortical areas, which distance remains constant for all types of triggers [2, 15]. The appropriate number of transmitter sensors and detector sensor pairs to isolate sufficient neural activity varies depending on the feature of brain signals used. For example, the prefrontal cortex, three emitters with eight detectors taking into account the typical distance may be enough to receive brain signals, allowing them to be decoded into BCI patterns [1]. In the case of real or imagined motor activity, 8 emitters and the same number of detectors are often used to cover the entire MC [15].

Previous experimental studies have shown a marked increase in hemoglobin concentration in the cortex ($p < 0{,}05$) in the imagined movement mode relative to the resting state [16]. Movement of the wrist in different directions elicits specific patterns of activation in MC [17]. The importance of studying brain function using fNIRS should consider not only the spatial domain but also the temporal characteristics of fNIRS recordings [18]. The reasons for the differences in the measured concentrations of oxyhemoglobin and deoxyhemoglobin are the result of asymmetry between the two lobes of the brain, where there are dominant zones and non-dominant zones [19].

The fNIRS method has strong potential, which increases the feasibility of its application for functional neuroimaging in populations such as infants, toddlers, and people with intellectual disabilities whose head movements are difficult to restrict due to compliance or communication limitations [20]. During visual brain activation, most of the activation appeared in the primary MC (Brodmann area 4). The pattern of brain activity was different in the four cases of wrist movement (Figure 2), in which patterns of hand movement in different directions could be distinguished. During right wrist movement, regardless of direction, brain activity in MC was paradoxically observed. Studies of damage to the functional zones of this systemic kinesthetic have been based on various methods e.g. on patients with brain lesions (physiology) and on anatomy [21, 22].

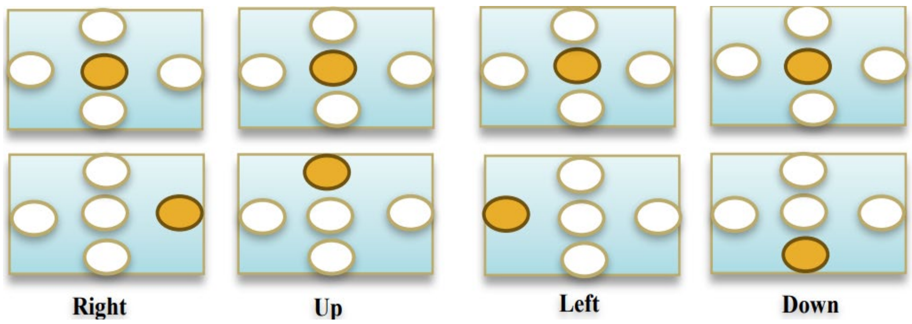

Figure 2 – Schematic representation of hand movement in different directions depending on visual triggers

Рисунок 2 – Схематическое изображение движения руки в разных направлениях в зависимости от визуальных триггеров

To date, several studies of motor function have mapped patterns of brain activation during exercise [23, 24]. These studies usually report that complex movements result in activation of motor regions and activation of primary MC and sensory areas. In addition to cortical activity, the dissymmetry of both sides of the brain and the prevailing asymmetry of the hand during human functional movement are inevitable. Numerous researches have proved noticeable differences in the patterns of motor activity of both upper limbs. Other studies have shown that the left hemisphere simply repeats actions. There are studies that have demonstrated that the left part of the brain simply repeats actions. While the division of the activity of the right hemisphere is carried out laterally when tracking tasks that require coordination of the visual cortex [25].

Physical motion and mental representation of motion

The pursuit of the mental representation of motion and its comparison with the physical representation of motion is the goal of modern neural interfaces strive for. If the mental motion representation is similar or close in accuracy to the physical motion representation, it is a logical and practical basis for opening valuable perspectives in control scenarios for neural prostheses [26, 27]. A mental representation of motion is defined as dynamic mental action without any explicitly corresponding physical motion. The effectiveness of visualization interpreted by the degree of functional equivalence between physical practice and mental simulation of the same movement [28]. Mental representations of movement show a similar tendency, but responses are slow and delayed by approximately 2–3 s compared to responses obtained during actual task performance [29].

The time intervals were different when subjects are given commands during motor tasks as well as during imagined tasks. Because each exercise includes a time interval for performing the motor task and a time interval for relaxation that is longer than the time interval for performing the task (Relaxation period > task period), the same is true for imaginary tasks. The time interval to perform a motor task may be 5 s, while the relaxation period is fifteen seconds. For the mental representation task to be successfully completed, the motor execution task is placed before the mental representation task [25].

Using fNIRS and HbO and HbR to analyze oxygen saturation to assess hand motor activity. Oxygen saturation paradoxically increases, reaches a maximum almost a few seconds after the command appears, and then decreases, reaching a baseline, which is an initial value that can be used to compare previous, current and expected future values, and this initial value set at a particular point in time. Maximum power appeared in the primary motor peripheral MC in the hemisphere opposite the effector terminal. In the left hemisphere, the right hand elicited a higher reaction than the left. In the right hemisphere, the amplitude of the remote remained the same for both hands. This means that the right hand being the dominant hand may require the involvement of additional neurons in the corresponding primary MC [11].

To date, various methods have been used, including calculating the average values of blocks of signal changes caused by a trigger, correlation analysis for the study of functional neural communication can be used average blocks, a general linear model is also used which considers systemic physiological signals as additional regressions, analysis of wave coherence, when applying signals of phase-based communication functions uses continuous wavelet transform, decomposition of the signal by inclined projections of the subspace [30–34]. Although fNIRS is mainly delicate to the haemodynamics of the superficial scalp and for leg and hand area detection, no significant statistical differences were recorded in cortical activity between automatic and non-automatic tasks, despite significant systemic free leg oscillations, which are sufficiently eliminated using all available short channels [35, 36].

fNIRS based on BCI

Understanding brain functions is important for effective application of BCI. Classification of brain states can be performed in real time according to recorded brain activity, triggered either by spontaneous physiological processes or by external stimulation, using an intelligent BCI system. BCIs are usually divided into two directions: the first, unidirectional, which receives signals from the brain or sends them to it, and the second, bidirectional, which allows the exchange of information in both directions, depending on the direction of their operation [37]. Near-infrared spectroscopy NIRS or optical tomography is a noninvasive technique containing the quantification of chromophore (hemoglobin and deoxyhemoglobin) concentration determined from the measurement of NIR light attenuation or temporal or phase changes. fNIRS estimates hemoglobin concentration from changes in absorption of NIR light. When light transmits through the head, there will be scattering or absorbing of light by the tissue through passing through it. Because hamoglobin is a significant absorbers of NIR light, changes in hemoglobin concentration can be reliably measured by knowing the amount of absorbed light.

At present, fNIRS technique is of interest to researchers in various fields that are interested in studying brain functions. This technique can be developed and used individually, or it forms an important combination with other medical imaging techniques, and this is indicated and documented by several studies of some recent researchers who are interested in studying brain functions [38–43]. The fNIRS requires at least one receiver and one transmitter to form a channel. Near infrared light is transmitted at two different wavelengths, as measurements are made at the capillary level, oxygen is exchanged. The depth of light penetration relies on the distance between the sources and the detectors.

Three fundamentals types of instruments are available for fNIRS technology: continuous wave (CW) emits light of constant intensity and measures differences in light intensity as it is refracted by the tissue [44], frequency domain (FD) emits modulated light intensity. As this light passes through tissue, its intensity and phase shift are measured [45], and time domain (TD) [46], short light pulses are generated and then the time taken for the photons to pass through the tissue is measured, requiring increasingly sophisticated equipment and processing procedures with providing more and more information about the properties of optical tissue.

Attenuation of light intensity can be measured only by conventional CW-fNIRS, whereas time-resolved FD and TD measurements indicate the time-of-flight of emitted photons-through the phase component of the complex FD signal and the function of the time spread of points in TD, where used to revitalize absolute absorption values and also to downgrade scattering coefficients [7]. Optical excitation (fNIRS principle) of a signal source will in turn result in a signal being received by the brain as a result of this excitation. This signal is not devoid of impurities, noise, artifacts, etc.

Consequently, the role of the signal processing (signal analysis) stage increases, which includes the stages of preprocessing, feature extraction and classification preceding the actual application stages. The main sources of noise are instrumental noise, experimental noise, and physiological artifacts. Methods for removing artifacts from the fNIRS signal are based on various methods of signal decomposition and transformation, and these methods have fairly high accuracy in selecting artifacts. For example, principal component analysis [47], wavelet transform [48], and feature reduction methods based on filters [49].

Although these methods exist, there are new approaches to data sanitization using a cumulative curve fitting approximation algorithm to filter the signals to decrease the effects of distortion due is based depends on the different types of filters used and there are ideal filters, but they are optimal [51], for a particular task and not ideal for all tasks performed by fNIRS. Hence, different filtering methods have to be chosen. The different stages of signal transmission from the data acquisition stage to the actual application are shown in (Figure 3). Assembly process of fNIRS optodes.

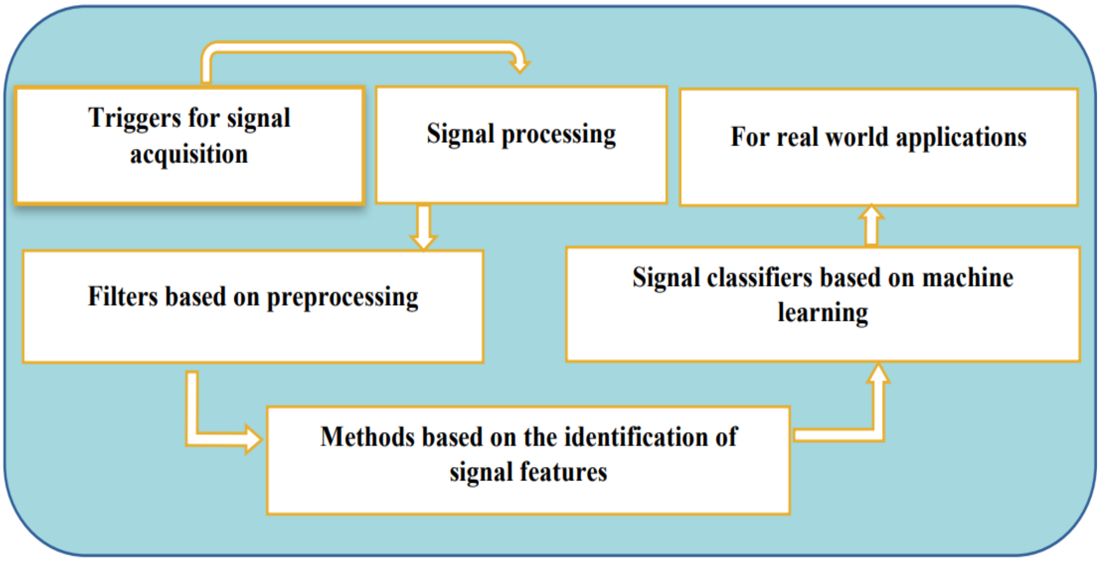

Figure 3 – Different stages of signal transmission
Рисунок 3 – Различные этапы передачи сигнала

When triggers are applied to a signal source, this signal goes through stages that can be summarized as follows:

Signal acquisition by fNIRS

At the stage of signal recording after the effect of triggers, several diverse experiments were carried out with the implementation of mental tasks and their goals were to deduce the different mental states measured according to different stimuli. Real movement and visual control tasks are most often used when performing tasks of intellectual fantasies.
The fact may lie in the fact that people's signal reactions are more reactive and more abundant with biological information during real body actions if they are compared with fully imagined mental tasks and for the same movement. This is where the difficulty of analyzing fully imagined and visually stimulated mental tasks in fNIRS-BCI stands out. It is noteworthy, that fully imagined mental tasks are necessary for those of you who suffer from closure syndrome in various daily communication applications [52].

Signal Processing

Using optical triggers, brain signals can be recorded by fNIRS, this signal is not free of noise impurities. The reason for the lack of purity of the signal may be due to a lot of different factors, such as laboratory conditions, hardware noise, as well as internal biological instructions and even unintentional external physical instructions that would undermine the purity of the signal.

In the effort to make this signal pure, there are many well-known techniques that have been used to separate digital noise as well as the presence of various filters. Such as the Butterworth frequency filter, Kalman filter, and others. For examples, when estimating the experimental workload [53] the Kalman filter has shown a promising improvement in performance. Despite the high quality of processing techniques and the presence of filters in their ideal states, the model of the dynamic model of the fNIRS signal remains difficult and complex, since providing a high correlation between the original raw signals and artificial signals is extremely difficult. This requires constant study to find a successful solution to this challenge to proceed with the concepts of smoothness in finding an already applicable pure signal. Therefore, a continuous search for an optimal solution is required in most cases, and this can be done by an optimal filter such as the Savitzky-Golay filter [54].

Other factors such as the Meyer wave and also artifacts of facial movement within a certain frequency range usually contribute to more noise. In contrast frequency-based filters, such as finite impulse response filters as well as Butterworth filters are used to separate these cyclic physiological signals . The frequency range for separating these signals is usually 0,2–0,6; 0,1; 0,6–2,5 Hz for the respiratory system, for the Meyer wave and for cardiac noise, respectively. Changes in blood pressure, vascular activity and carbon dioxide concentration the frequency of the noise zone is usually 0,01–0,15 Hz [55]. Recording the response of the brain from the surface layer is the task of short channels in the fNIRS used, where they involve a pair of source and optics with a typical distance of 0,5–10 mm, as shown in (Figure 4).

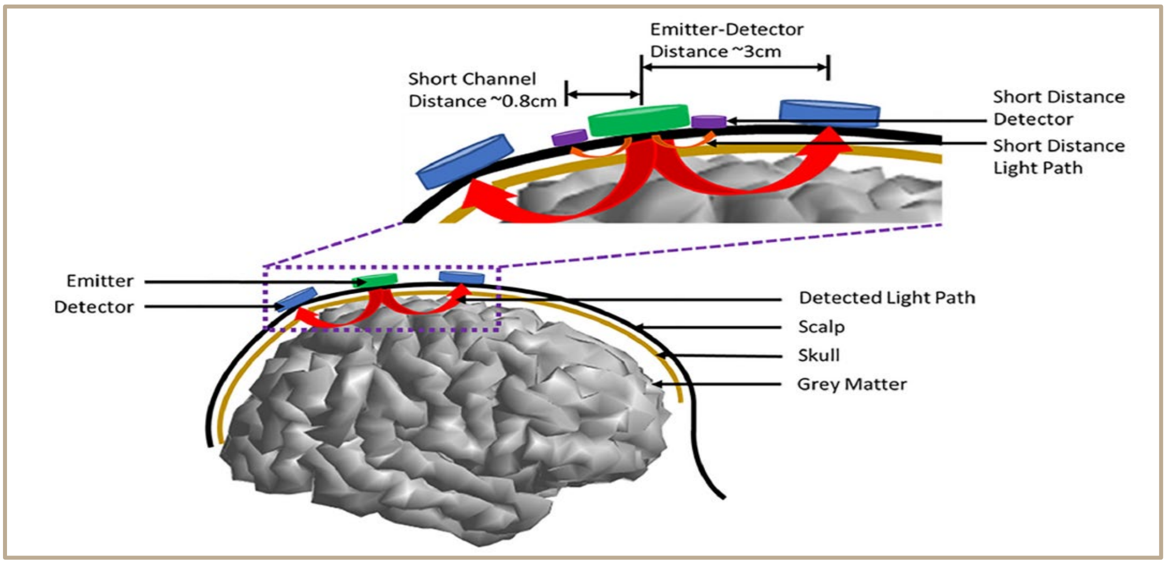

Figure 4 – Short channel signal acquisition block based on fNIRS probe and according to typical distances
Рисунок 4 – Блок сбора сигнала короткого канала на основе датчика fNIRS и в соответствии с типичными расстояниями

Noise suppression in the main components of the short channels of the fNIRS probe can be carried out using different approaches, either independent or combined approaches [56–58].

Feature extraction

Feature extraction is a type of abstraction, a dimensionality reduction process in which the original set of original variables is reduced to more manageable groups (features) for further processing, turning domain-specific data into model-understandable vectors while still being sufficient to accurately and completely describe the original data set. In addition, during the feature extraction phase, and as a method of encoding the fNIRS haemodynamic response to four other parameters are vector angle and blood flow vector magnitude, cerebral oxygen metabolism, and cerebral blood volume. The vector phase analysis can be used as a method of encoding the haemodynamic reaction. It has been confirmed that the use of vector phase analysis functions in the BCI system can superior statistical methodologies. Improving the accuracy of the model by at least 20 %, which has proven when using vector phase study functions, and this ratio was compared with statistical models of BCI in the binary classification of "mental activity versus rest" [59]. Feature extraction is used in machine learning (ML), pattern recognition, and image processing.

After the data acquisition and processing stage comes the feature extraction stage, which is used in ML, pattern recognition and image processing. Feature extraction can be either temporal or statistical features in the time domain and can vary depending on the triggers that activate MC for each action. In various scientific experiments utilizing fNIRS to obtain brain signals in the presence of various triggers, these signals are accompanied by the aforementioned noises, hardware noise and others, which means that the raw signals from fNIRS data are unsuitable for use as classification features.

Thus, feature extraction is an important process in selection-based taxonomy. Because fNIRS data are time series data, statistics obtained over specific time periods were often calculated as features. Many methods have been used for feature extraction. In most previous works the predominant approach was manual feature creation, then methods based on the convolutional neural network (CNN) became the best approach used for feature extraction [60].

fNIRS has low signal performance beacuse of variable signal to the ratio of noise, the coefficient of variation can be utilized to eliminate channels and experiments with low level signal quality in diagnosing mild cognitive impairment preceding Alzheimer's disease by placing measurement sources on the scalp to measure chromophore changes in the prefrontal cortex and parietal zone joining cortex to cognitive function [61].

Classification

Machine learning method as a classifier is crucial for providing high classification accuracy in fNIRS-BCI. In all fNIRS-based experiments, after extracting features from fNIRS data, a classifier is needed for feature assignment, identifying motor activity categories (patterns), and then for the practical application phase. It is the goal and success of every scientific experiment to crown it with practical application to reality. The continuous development of fNIRS together with ML algorithms can greatly enhance the implementation of fNIRS monitoring at the clinical level and facilitate the overall interpretation of fNIRS signals [62]. It is noticeable that plenty works employ fNIRS signals with deep learning techniques for many diagnoses, and of course these works are accompanied by many challenges, this may be including cortical analysis and BCI [63–65]. For example, using fNIRS based on BCI and motor imagery trigger to reduce the confounding effects of breathing, a linear discriminant analysis model is used as a classifier [66].

Discussion

According to a study of scientific manuscripts from the last decade based on a comparison of cortical activation triggers, primary MC activity is associated with mental representation of movement, planning, and control. Triggers for cortical activation vary depending on the nature of the action, whether emotional, pathological, or other activity assessment. The observed characteristic circadian patterns are evident in feedback to different emotional triggers with objective identification and characterisation of patterns of neural activation associated with different emotional states. Note that the effects of triggers on the cerebral cortex (in general) were not the same for different subjects and even for the same subject. For example, upper limb tasks are the most obvious, especially during motor activity.

The activation patterns of the both lower limbs were found to be very similar in both images (motor and mental) [36]. The results of triggers that activate MC when learning hand movement (unclenching and pressure on the hand) during movement may differ compared with the results of triggers, whether sound, mental or other, depending on the degree to which the cortex is more activated and thus receives more cerebral information.

This is something that could be indicated and recommended in future studies to identify the preference of triggers for MC activation, whether motor, mental triggers, imagery. This suggests that future work by those interested in neuroimaging techniques, as well as a high level of interest in advanced signal processing techniques or improved subject training, may be required to reliably distinguish between these triggers.

Conclusion

Indeed, according to scientific studies and experimental investigations specialized in the study of brain functions and what is present in the axes of the scientific field, the fNIRS technique is one of the pioneering techniques interested in the study of brain functions and, in particular, the recording of biological signals derived from triggers that activate the MC.

When triggers are presented, the activity recorded in the MC is associated not only with the performance of a physical movement, but also with the occurrence of that activity when a similar mental representation of that movement is performed. Although all triggers result in activity in the MC, be it physical representation or mental, there are differences due to dominant and non-dominant lobes of the brain, differences between the upper limbs where physical representation is more pronounced, and differences in the lower limbs when comparing automatic and non-automatic movements, albeit with a small difference.

To summarise, even at the level of MC activation, differences are evident in the application of commands, whether motor or mental commands. These differences need a lot of research to prove their validity and how to approximate them, taking advantage of the results of artificial intelligence in the role that artificial networks play, and this will be a positive indicator when dealing with triggers based on positive results that are in the interest of clinical applications, especially in prosthetics, psychological research and others. Moreover, It should be revealed that targeted activities that stimulate the MC can be used as a therapeutic method in the practice of occupational therapy, and this may give it an essential role in the health insurance system.

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