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A. M. SAMANDARI

Belgorod State National
Research University,
Belgorod, Russia

PROMISING SYSTEMS FOR CONTROLLING PROSTHETICS: A REVIEW

People with disabilities in the enormous scientific-technological revolution hope that it will overshadow the provision of assistance and find suitable solutions for them to lead their normal lives. The intersection of sciences among themselves took into account the problem of physical disabilities and, in particular, the loss of both upper and lower limbs. Modern prostheses are the product of the intersection of science and the technological revolution, which are still in the ladders of modernity and development due to they contain operators that can be controlled by brain signals according to the principle of neurainterfaces. Neuroimaging techniques such as electromyography, functional infrared spectroscopy and electroencephalography are the superior methods of controlling these modern prostheses can be modelled on two functions, namely independent work and hybrid work. In light of these data the article takes upon itself these systems in their individual and hybrid states. In addition, this article indicates which of these techniques is the most worthy in creating the preferred system. The scope of the research methodology limited to neuroimaging techniques towards scenarios of neurological rehabilitation and restoration of lost functions. The review has three axes. The first axis collects, summarizes and evaluates information from relevant studies published over the last decade. The second axis presents important results from previous experimental results in this field in relation to current research. This study was systematically conducted to provide a rich image and evidence-based evidence of prosthetic control techniques to all experts and scientists. The third axis is to identify a wide area of knowledge that requires further investigation, and follow-up the succession of scientific events of these systems towards the possibility of integration among themselves to create the most promising system for controlling prostheses.

Keywords: disability, electroencephalography, electromyography, functional near infrared spectroscopy, hybrid brain-computer interface, control system, operators, prostheses.

Introduction

Our concrete world, which has become inflamed by wars with modern and deadly lethal weapons, indicates that disabilities are constantly increasing and significantly. In order to diagnose the focus of the research we take in consideration the disabilities that can be seen in the upper limbs are present in five essential regions [1]:

1. Wrist amputation.
2. Forearm amputation.
3. Shoulder amputation.
4. Shoulder joint amputation.
5. Forequarter amputation.

Disability or loss of a body part is a difficult psychological blow to a person, which causes anxiety, stress and depression, has a strong impact on a person's personality and may even lead to suicidal thoughts. In order to put the disability of the limbs, in particular, the upper limbs, as a research problem, it is necessary to work on finding alternatives using concerted efforts and cooperation and taking advantage of the accelerated technological progress to improve the lives of the missing limbs.

Previously, the prosthesis served only a cosmetic purpose, and after technological progress entered, the prosthesis was blended to be a hybrid between aesthetic and functional performance. To control the functional performance, it is necessary to control the triggers of the prosthesis. Modern neural interfaces play the role of controlling these operators that — neural interfaces — based on the real-time detection of patterns of motor activity of the brain using neuroimaging techniques on the one hand and the transformation of the information obtained into commands for controlling the example of a prosthesis on the other [2, 3].

Brain — computer interfaces (BCIs) can be defined as neural interfaces that keep pace with modern technical development, which are innovative in measuring brain activity and transferring commands to a computer or an external device, and they are based on controlling machines and other devices using only what the operators think (using only their thoughts). BCIs in terms of operation, there are two different systems, namely

— unidirectional its action is limited to either receiving signals from the brain or sending signals to the brain;

— bidirectional allowing the exchange of information in both directions, thereby controlling external devices [4].

It should also be noted that neural interfaces can be classified depending on the nature of the work, whereas recent studies have proven the possibility of forming another system of neural interfaces called hybrid brain-computer interface systems, which abbreviated as hybrid brain–computer interfaces (HBCIs). In terms of data processing the work of HBCIs is extends to hybrid double and triple data processing and is not limited to single data processing [5], [6–8]. Neuroimaging methods can be based on BCIs or HBCIs. Currently, the most prominent and popular methods for controlling neuroprostheses neurorehabilitation are electroencephalography (EEG) [9, 10], functional near infrared spectroscopy (fNIRS) [11, 12], and electromyography (EMG) [13, 14].

As documented by recent experimental studies, the most common methods are (EEG, fNIRS and EMG), which are of great interest in the fields of prosthetics. It should be noted that these methods (when used independently) cannot form an integrated system and this is due to several inherent disadvantages. However, what distinguishes these methods is that they can be one that can fill the shortcomings of the other with which they share in the composition of the hybrid system. On the related hand, the fNIRS technique is one of the most important ways to form a hybrid system, as it does not depend on muscle activity. The absence of muscle activity or muscle lethargy, or their inability to cause a deficiency in EEG and EMG techniques.

Similar, the article sheds light on adored technologies in the control framework on external devices and diagnoses their superiority and non-superiority towards HBCs based on the most important studies that have dealt with these technologies whether used in the individual state or in their hybrid state. In addition, this article encourages those interested in scientific research related to prosthetic control systems, exoskeletons and in general devices that can be controlled through the biological imagination. The product of scientific progress of medical devices overshadowed the improvement and management of prostheses in terms of aesthetics and functionality [15]. Thus, the classification of human-machine interaction strategies is influenced by recorded brain signals that are well-known tools for studying brain functions and which are in the depth of the growing scientific research axes. In turn, neuroimaging techniques that come into significant contact with prosthetics have emerged.

EEG is one of the first neuroimaging techniques proposed and mastered. It is used to record physiological signals during brain activation to represent hand movements as a procedure for controlling prostheses particularly, the upper limbs [16]. Electromyography (EMG) is another pioneering technique using electromyography for controlling external devices [17] and neurorehabilitation [18]. fNIRS is a powerful tool for studying brain activity, more widely used in current research and in various fields [3]. Despite the relative successes achieved by the above techniques, they cannot be considered as promising and ideal ways to control prosthetic limbs due to the drawbacks associated with them. Similarly, this review deals with future perspectives that strengthen the concepts of finding a promising prosthetic control system.

Scope of research methodology strategy

The ultimate goal of this review is to analyze and compare the systems and research studies in the field of prosthetics in order to consolidate the idea of finding an integrated and promising control system

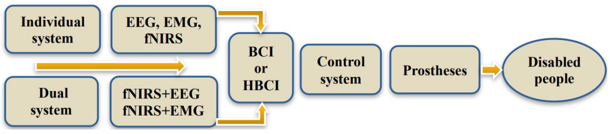

Fig. 1. Research methodology for the most common systems for prosthetic scenarios

for the prosthesis. The methods varied from databases such as Google Scholar, eLIBRARY, Scopus and various websites such as https://www.refseek.com, https://www.base-search.net and others. The scope of the research strategy and methodology involved hundreds of up-to-date sources for 95 % (2020–2024) and was reduced to 67 sources.

The sequence of searching for technical systems, both individual and combined, up to the control system of the prosthesis can be indicated in Fig. 1.

Conclusion the research methodology focused on the topics of the article and its keywords, the recommendations of experienced researchers and the usefulness of their observations, and then added or deleted them to reach the target purpose.

Hybrid brain–computer interface (HBCI)

The concept of BCI is related to the fact of recognization of data in real time and this is considered an essential requirement for controlling the prosthesis. BCI is located at an interdisciplinary concept as it includes engineering, computer science, biology and physics but its development is closely and really related to physics. Spontaneous physiological processes or processes resulting from external stimulation lead to the classification of brain states according to its recorded activity in real time using an intelligent BCI system. The reception of signals from the brain, sending them to it, or allowing the exchange of information carried by these signals in both directions depends on the work of HBCI [19], and can be classified as the following [3, 4]:

BCI based on the control command. The neural interfaces are classified based on the active-reactive and passive mode or they may be dual-mode and this depends on the control commands provided by BCI operator.

BCI based on the way the input data are processed. Synchronous and asynchronous this depends on the input processing method.

BCI based on invasive and non-invasive BCI and brain–machine interfaces. Electrophysiological recordings may be classified as non-invasive or invasive, but it is the most promising system for controlling prostheses based on non-invasive (the purpose of the current article).

HBCI includes single data processing, or extends to double and triple data processing and this is what makes it a hybrid system [20, 21–23]. According to the principles of operations that may be related to electrical activity, chemical processes of the brain or others, one of the highest goals of HBCI is to control prostheses or external devices in general using brain electrical activity in the form of EEG [24] or chemical activity in the form of fNIRS [25, 26], when used alone or in combination [27]. A large percentage of PSI systems use only one type of physiological signal, whereas fNIRS method is able to take advantage of different methods and thus can combine active and passive neural interfaces.

Active and passive HBCI systems are more efficient, allow assessing the mental state of the human or animal and take benefit of various systems such as fNIRS and EEG [24, 28, 29] as well as EEG-EMG hybrid technologies [30, 31]. In the context of hybridisation systems HBCI can be of three types according to different brain activity signals:

I. HBCI when using various signals of reflex brain activity.

II. HBCI when using signals of brain activity mixed with external signals of a different nature.

III. HBCI when using various physiological brain activities simultaneously is synchronized with the recording technology.

The performance of hybrid BCI provides a higher rating accuracy than individual BCI. Therefore, one of the fundamental reasons for not adopting HBCI on a large scale in the bulky and complex equipment. To decipher this complexity, lightweight and compact HBCI needs to be implemented with caution to reduce performance degradation. In this line of research studies have shown that the use of HBCI with only two EEG channels and two pairs of fNIRS (detectors sources) can achieve high accuracy while the system is easy to use [32].

The most common systems in prosthetics scenarios

In its independent state

EEG

EEG is a non-invasive method that depends on the nervous system by stimulating its electrical activity, and the information recorded by EEG and obtained between the brain and the device as a result of electrical activity is still low. EEG has proven itself in several areas, particularly in clinical applications [9, 10, 33], but due to highly sensitive to artifacts and noise, which makes it unsuitable as a control system for prostheses when it is in its independent state [16]. However, experimental studies have recently been conducted to design and implement a prototype artificial lower limb controlled by brain signals recorded by EEG [34].

Advantages:

a. Low cost.

b. Portable, non-invasive and easy to use.

c. Can provide high temporal resolution of brain activity.

Disadvantages:

a. Low spatial resolution due to wide distribution of electrodes on the scalp.

b. Susceptible to artefacts associated with eye movements, muscle contractions, etc.

EMG

EMG is a diagnostic method that works according to the principle of skeletal muscle activity to record vital signals resulting from muscle activity. When its work is limited to measuring the electromyography of the surface muscles resulting from the muscular structure, it is called surface electromyography and is denoted by the symbol (sEMG). The measurement can be achieved either invasively or superficially (non-invasively), at the level of a single muscle fiber, a single motor unit or the entire muscle. EMG information processing permits diagnosing musculoskeletal and neuromuscular disorders and analyzing or using simg for rehabilitation or robot control [14, 35].

Advantages:

a. Extremely high temporal resolution.

b. Excellent source localization capabilities.

Disadvantages:

a. Requires expensive equipment to be set up and operate.

b. Requires highly trained personnel for proper calibration and signal processing.

Fig. 2. Simplicity of the work, showing a subject performing experimental tasks in a laboratory at Belgorod State University in Russia in pursuit of finding a control system for prostheses

c. Susceptible to environmental interference, such as electromagnetic fields generated by nearby electronics, which can distort readings if not properly shielded from these sources before taking measurements.

fNIRS

fNIRS is a non-invasive (neuroimaging methods for BCIs) optical imaging technique that typically uses two or more different wavelengths to measure changes in the concentration of oxygenated hemoglobin (oxyHb) and deoxygenated hamoglobin (deoxyHb) (650–1000 nm). However, several aspects that probably make fNIRS more useful for evaluation in conjunction with EEG, sEMG, functional magnetic resonance and positron emission tomography include its usefulness depended on usability as well as indicators that oxygen saturation of brain capillaries observed with fNIRS mostly reflects neuron activity [36, 37]. fNIRS can only be measured in areas close to the surface of the cortex and can also be referred to as optical topography (OT) and sometimes simply as NIRS (Fig. 2).

In addition, several experiments utilizing fNIRS for prosthesis control have been relatively successful [1, 12].

Advantages:

a. Portable and low cost compared with other BCI technologies.

b. Highly sensitive and capable of detecting changes in oxygenated blood levels at different depths of brain tissue with good accuracy when properly calibrated.

Disadvantages:

a. Lower temporal resolution than EEG or MEG systems due to their reliance on haemodynamic responses rather than electrical signals directly from neurons.

b. Not suitable for measuring deep brain structures because it depends on the transmission of light through the skull, which is known for the hardness of its bones, which leads to obstruction of light in thick skulls or dense skeletons, as in the elderly or under 5 years of age in children.

Results of previous studies of the system in its individual state that used the most common classifiers, such as, Support Vector Machine (SVM), K Nearest Neighbor (KNN), linear discriminant analysis (LDA) and others are shown in Table 1.

Hybrid state of fNIRS + EEG

The basic idea of creating any hybrid system, be it technical or software , is that one of the two systems should be complementary to the shortcomings of the other, so that the output of the hybrid system should provide results that are superior to those of the stand-

Table 1

Classification accuracy results for systems (independent usage)

Reference and publication year	Independent system	Method	Accuracy
[38], 2021	EEG	End-to-end shallow architecture	83,20 %
[39], 2022	EEG	Multiple built-in transfer training	83,14 %
[2], 2021	fNIRS	NN_LSTM, NN_ConvLST, NN_ResNet	91 %
[40], 2020	fNIRS	Linear discriminant analysis, support vector machine and k nearest neighbor	90,54 %
[41], 2017	EMG	SVM, LDA	72,2 %
[35], 2023	sEMG	CNN-LSTM	70 % : 30 %

Table 2

Classification accuracy results for systems (hybrid usage)

Reference and publication year	Hybrid state of system	Method	Accuracy or average value of accuracy
[56], 2022	EEG+fNIRS	Vector-phase analysis	82, 89, 87, 86 %
[57], 2022	EEG+fNIRS	fNIRS-driven attention network (FGANet)	78,59 % ± 8,86
[45], 2023	EEG+fNIRS	FBCSP+PCA+SVM, GLM+MBLL	92,25 % ± 4,99
[41], 2017	sEMG+fNIRS	SVM, LDA	86,4 %
[58], 2021	sEMG+fNIRS	LDA	96,4 % and 94,1 %
[59], 2020	sEMG+fNIRS	LDA	78–81 %

alone system. On the other hand, it should be that two candidate systems for the formation of the hybrid state are similar in some characteristics with the possibility of compensating for their shortcomings with each other.

As mentioned above, fNIRS technology is the technology that conforms to this vision, it can be considered as a complementary tool to fill the shortcomings of the common technology. Thus, the possibility of creating a hybrid system of fNIRS+EEG is possible to obtain, since the results obtained with these systems are better than those obtained when used independently (Table 1, 2).

In EEG, sensor-electrodes are located on the skin of the upper part of the skull (according to international «10–20» system) and pick up electrical signals from neurons in the brain. This leads to the fact that the electroencephalography of the brain can be measured and at once allows monitoring complex nervous activity as well as tracking its continuous changes [3]. EEG is also positive in some characteristics as well as it is negative in some characteristics, for example, it is non-invasive, provide high temporal resolution and allowing real-time measurement of motor imagery in its positive sense [42], while it is very sensitive to noise in its negative sense, and this is what makes it under study and to say a complementary tool, and fNIRS may be an alternative to it for some functions or these two technologies may have a unified system that complements each other.

In contrast to fNIRS, which suffers from a time delay of 3–5 seconds in detecting regions of brain activity. It has also been extensively reported that better BCI performance can be performed by using multimodal analyses instead of offline EEG signals. For this, numerous studies evaluating both the electrical activity of the brain and the activity of the circulatory system attracted considerable attention [43, 44]. Furthermore, recent scientific studies based on the analysis of activated brain regions using fNIRS proved that the accessory motor cortex was obviously activated during motor imagery, which leads that hybrid signals with hybridisation strategy can improve stability and error neglect in BCI systems, this makes it a valuable way for practical applications [45].

The accuracy of classification and the rate of information transfer by the method of the combination of EEG-fNIRS due to their complementary characteristics are from the widespread indicators in our current time [22]. The combination of these technologies has certain unique characteristics because the basis of merge them is their dependence on a physiological phenomenon called neurovascular coupling in the brain, which makes them more useful in certain applications. The system of the two technologies is promising for prosthetic control [46]. Therefore, in the foreseeable near future, a possible alternative to EEG for recording brain activity in a mobile handheld BCI can be considered as fNIRS technology or a form of hybrid EEG-fNIRS method.

Hybrid state of fNIRS + EMG

EMG information processing enables the diagnosis of muscle and neuromuscular disorders, as well as analyze or use sEMG in various fields for example robot control, rehabilitation and others [47, 48]. Their frequency ranges vary from 0,01 Hz to 10 kHz and this certainly depends on the type of study carried out by EMG. According to recent studies, frequencies between 50–15 Hz are the most useful [49]. Whereas with fNIRS, the frequency is approximately 1 Hz at optimal wavelength 830 nm [3, 50]. At the same study, sEMG and fNIRS can be used together or used independently, but when they are used together the dual system excels.

In the field of motor activity, several studies carried out through the techniques of fNIRS and EMG have shown that there is no relationship to the signals obtained during dynamic movements when performing sports exercises, in addition, even the methods of signal analysis cannot be described. In [51], found that it is possible to perform simultaneous measurements of EMG, mechanomyography (MMG) and near-infrared spectroscopy (NIRS) at a local position using a multi-layered wireless sensor that can be used to predict muscle fatigue. In the dynamics of running on a treadmill and strength exercises a recently developed integrated quadriceps oximetry system was implemented in which regional muscle oxyhemoglobin saturation and sEMG data were measured [52].

Positive correlations were found between the EMG signals and the fners during the recording of oxygen consumption and muscular activity of the left calf muscle among the participants, where the signal correlations are with the most active and least active lifestyles [53]. This leads to a correlation during dynamic movements in the signals of EMG and fNIRS during exercise.

The existence of these associations, which can be described as positive and important, is a clear guide towards the formation of a hybrid system, which is what this article seeks and this quest is extended to further laboratory studies in order to investigate the relationship between brain activity and the performance of motor tasks and can be targeted for clinical trials.

In the operation of the EMG system alone, improvement in control performance requires the addition of more EMG sensor nodes, but this method is immaterial and impractical for people with limb disability due to atrophy or insufficiency of the remaining muscles [54]. Additionally, prostheses should be lightweight, but the improvement in control performance is offset by complexity, excess weight and a more expensive price when adding sensory nodes, whereas in the philosophy of prosthetics control interfaces should be very perfect, limited sensory channels and computational complexity [55]. Results of previous studies of systems in their hybrid state that used the most common methods and classifiers are shown in Table 2.

Hardware, software and algorithms used for signal processing

When the brain is activated by any of the triggers, the signal reception stage begins. The acquired signal is impure mixed with noise, artifacts and other effects, therfore, the acquired signal goes through different stages and here the role of artificial intelligence represented by neural networks enters towards filtering, analysis and classification up to the stage of real-world application. All triggers of the motor cortex with different commands cause a change in hemoglobin concentration based on the stimulus that triggered brain activity. The triggers to activate the motor cortex should be motor triggers. What we would like to point out is that the signal dynamics obtained using hybrid systems concepts go through the same steps as the signal dynamics obtained using independent systems concepts, as shown in Fig. 3.

A modern (software and hardware-based BCI) is a system based on artificial intelligence that can process

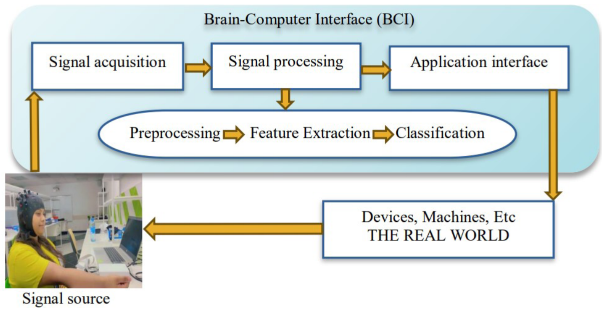

Fig. 3. Dynamic stages of the signal

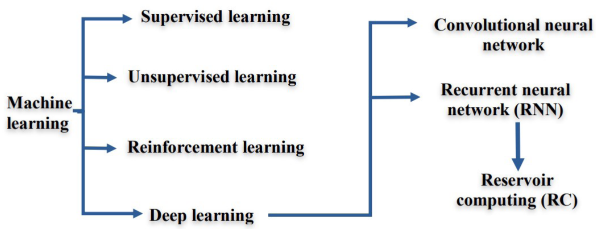

Fig. 4. Basics of machine learning in its four strategies

brain activity in real time and recognise a certain finite set of central nervous system activity patterns [2].

One of the current and promising approaches to analysing neurophysiological signals is machine learning are machine learning (ML) and reservoir computing (RC). Machine learning approaches have traditionally fallen into four broad categories, depending on the nature of the input data and the learning strategy shown in Fig. 4.

These methods involve analyzing data without prior knowledge of the data source, i.e., data not associated with the model. In other words, the underlying mathematical model (or dynamical system) that generates the time series is unknown. At the same time, machine learning can build this model from sampled data, known as 'training data'. Thus, these methods, trained on a reasonable and representative amount of training data, can perform various tasks (classification, detection, prediction) based on the newly acquired data [3].

The challenges can exist at any stage of the signal, feature extraction is also not without challenges because it depends heavily on previous complex knowledge over time, and this leads to the risk of losing the information that the biological signal carries [60, 61]. Feature extraction methods vary from one technique to another, some pass through multiple stages, such as EEG, where brain signals can be filtered in three bands, and some are limited to one stage, such as fNIRS, where brain signals can be filtered in one band to improve signal quality for later analysis [45, 62].

Apparently the language of hybridisation is not limited to technology, but this can also extend to signal program stages. In [43], a combination consisting of wavelength range decomposition with canonical correlation analysis to correct for motion artifact of single channel EEG and fNIRS signals performed better than using wavelength range decomposition independently.

The performance preference of single-method and mixed methods using the conventional whole optimization algorithm the classification accuracy was equal to 90,37; 7,66 % and binary improved whale optimization algorithm showed high classification accuracy equal to 94,22; 5,39 % which means that the classification performance increased by 3,85 % compared to the traditional whale optimization algorithm [63].

Discussion

Perhaps the most prominent systems in the fields of scientific research and the most common towards the transformation of mental commands into movement are EEG, EMG and fNIRS. These technologies with their individual uses face a clear deficit in the formation of a comprehensive system but these systems can be combined to create an integrated control system. For example, both EEG, EMG rely on muscle activity, whereas muscle activity may not be available if the muscle is damaged or lost [64, 65].

The fNIRS technique is based on chemical processes (blood oxygen level independent (BOLD). That means meauring the concentrations of hemoglobin and deoxyhemoglobin in the sense that they do not depend on muscle activity and therefore can share their positive characteristics to compensate for the negative characteristics in the EEG technique or the EMG technique.

After a detailed breakdown of the advantages and disadvantages of the above methods by comparing the results of the technologies found that the hybrid prosthetic management system produced more accurate results than each system individually [66]. The most likely advantage of the hybrid system is that one of the two technologies compensates for the shortcomings of the other. In the case of the software system, the results of the binary logarithms were better than those of the individual logarithms [67]. Thereby, it is concluded that the results obtained with hybrid systems hold great promise and are extremely encouraging for the development of a (software-based) prosthetic control system.

Conclusion

Accurate control of prosthetic limbs is one of the biggest challenges currently existing in the scientific field. Measuring brain activity and translating it into commands to control machines and devices using only thoughts is extremely difficult. However, modern technology has penetrated significantly in this field and has made impressive progress, particularly in machine learning and related branches such as neural networks and others and their relationship with medical methods as EEG, EMG and fNIRS. Each of these methods has its own characteristics and shortcomings that have led to its lack of effectiveness in controlling prosthetics. A hybrid system of these technologies may be a solution for achieving higher efficiency in prosthetic control.

It should be noted that future developments for a hybrid system of prosthetic control are not limited to the mentioned technologies but may extend to other technologies as well. EEG, EMG, and fNIRS techniques have proven to be relatively successful in prosthesis control. Additionally, fNIRS is most convenient when combined with EEG and EMG as confirmed by numerous recent studies. In the future, this will be an incentive to investigate these techniques independently or in hybrid form, as they are the closest and most convenient to address each other's shortcomings, leading to a successful hybrid prosthesis management system.

Therefore, it can be summarized more succinctly as follows:

— EEG, EMG and fNIRS systems are still in their individual state in the circle of research and experimental studies in endeavouring to find a control system for prosthetic limbs.

— The combination of EEG with fNIRS is more superior than the individual system (when EEG is used individually or fNIRS is used individually).

— The combination of EMG with fNIRS is more superior than the individual system (when EMG is used individually or fNIRS is used individually).

— The principle of operation of EEG, as well as EMG depends on muscular activity, and this activity may not be available, while the principle of operation of fNIRS is based on chemical processes that makes it the most suitable to be a complementary tool with EEG or with EMG to create the most promising system for controlling and restoring lost functions.

— There are no studies that indicate the superiority of the EEG with fNIRS system over the EMG with fNIRS system and this is a positive indicator for future studies to find a standardised and comprehensive control system for prosthetic limbs.

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SAMANDARI Ali Mirdan, Graduate Student, Belgorod State National Research University, Belgorod.
Correspondence address: aliofphysics777ali@gmail.com

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САМАНДАРИ АЛИ МИРДАН

Белгородский государственный
национальный исследовательский университет,
г. Белгород

ПЕРСПЕКТИВНЫЕ СИСТЕМЫ ДЛЯ УПРАВЛЕНИЯ ПРОТЕЗАМИ: ОБЗОР

Люди с ограниченными возможностями в условиях стремительной научно-технической революции надеются, что она преодолеет лишь оказание им поддержки и найдет подходящие решения, чтобы вести нормальную жизнь. Взаимодействие наук между собой учитывает проблему физических недостатков и, в частности, потерю как верхних, так и нижних конечностей. Современные протезы являются продуктом пересечения науки и технологической революции и все еще находятся на пути своего становления, поскольку содержат исполнительные механизмы, которые могут управляться сигналами мозга по принципу нейроинтерфейсов. Методы нейровизуализации, такие как электромиография, функциональная инфракрасная спектроскопия и электроэнцефалография, являются превосходными методами управления этими современными протезами, которые можно смоделировать по двум функциям, а именно по независимой работе и гибридной работе. В свете этих данных статья рассматривает эти системы в их индивидуальных и гибридных состояниях. Кроме того, в статье указывается, какой из этих методов может быть выбран в качестве предпочтительной системы. Область применения методологии исследования ограничена методами нейровизуализации в отношении сценариев неврологической реабилитации и восстановления утраченных функций. Обзор имеет три направления. Первое направление собирает, обобщает и оценивает информацию из соответствующих исследований, опубликованных за последнее десятилетие. Второе представляет важные результаты предыдущих экспериментальных результатов в этой области в отношении текущих исследований. Исследование было проведено систематически, чтобы предоставить всем экспертам и ученым полное представление и основанные на доказательствах методы управления протезами. Третья часть заключается в выявлении широкой области знаний, требующей дальнейшего изучения, и отслеживании последовательности научных достижений в этих системах и возможности интеграции между собой для создания наиболее перспективной системы управления протезами.

Ключевые слова: инвалидность, электроэнцефалография, электромиография, функциональная инфракрасная спектроскопия, гибридный интерфейс мозг-компьютер, система управления, операторы, протезы.

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САМАНДАРИ Али Мирдан, аспирант Белгородского государственного национального исследовательского университета, г. Белгород.
Адрес для переписки: aliofphysics777ali@gmail.com

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