УДК 617.57.77
DOI: 10.26102/2310-6018/2024.44.1.005

Functional near-infrared spectroscopy (fNIRS) as a hybrid system: a review

Ali M. Samandari

Belgorod State National Research University, Belgorod, the Russian Federation

Abstract. Sensor devices and biomedical imaging technologies used in clinical application scenarios are essential for providing a comprehensive portrait of patients' state, but these technologies, despite their outstanding advantages, have their inherent disadvantages. Beginning with the principle of complementary images of medical imaging techniques, this review examines the functional near-infrared spectroscopy (fNIRS) technique and its use as a hybrid system. The fNIRS technology delivers impressive results in terms of the biological signal classification accuracy, but its use as a hybrid system with electroencephalography (EEG) and electromyography (EMG) achieved better results because it has become a complementary tool to fill the deficit of the common technology with it, and this has been highlighted in this review. The results show that the superiority in the biological signal classification accuracy provided by hybrid systems from fNIRS with EEG and EMG would provide a comprehensive and objective assessment of the patients' state from the stage of illness to healing. In conclusion, we have no indication from the scientific studies of the previous four years (2020–2023) that demonstrate which of the hybrid systems is better than others when used in clinical practice, and this encourages further in-depth studies to validate the combination of methods to prove their success and preference.

Keywords: HBCIs, fNIRS, fMRI, EEG, EMG, MEG.

For citation: Samandari A.M. Functional near-infrared spectroscopy (fNIRS) as a hybrid system: a review. *Modeling, Optimization and Information Technology*. 2024;12(1). URL: https://moitvivt.ru/ru/journal/pdf?id=1459 DOI: 10.26102/2310-6018/2024.44.1.005

Спектроскопия в околоинфракрасном диапазоне (fNIRS) как гибридная система: обзор

Али М. Самандари

Белгородский государственный национальный исследовательский университет, Белгород, Российская Федерация

Резюме. Сенсорные устройства и технологии биомедицинской визуализации, используемые в сценариях клинического применения, необходимы для получения полной картины состояния пациентов, но эти технологии, несмотря на их выдающиеся преимущества, не лишены недостатков. Исходя из принципа взаимодополняемости методов медицинской визуализации, в этом обзоре освещается функциональная технология ближней инфракрасной спектроскопии (fNIRS) и ее использование в качестве гибридной системы. fNIRS технология достигла впечатляющих результатов с точки зрения точности классификации биологических сигналов, но ее использование в качестве гибридной системы с электроэнцефалографией (ЭЭГ) и электромиографией (ЭМГ) позволило достичь более высоких результатов, поскольку она стала дополнительным инструментом для восполнения дефицита другой технологии, и это подчеркивалось в рамках настоящего обзора. Полученные в ходе исследования результаты показали, что превосходство в классификации точности биологических сигналов, обеспечиваемых гибридными системами от fNIRS с ЭЭГ, ЭМГ, обеспечило бы всестороннюю и объективную оценку состояния пациентов от стадии заболевания до выздоровления. В научных исследованиях предыдущих четырех лет (2020–2023 гг.) нет указаний на то, какая из гибридных систем лучше других при использовании в клинической практике, и это побуждает к дальнейшим углубленным исследованиям для проверки комбинации методов, чтобы доказать их успешность и предпочтение.

Ключевые слова: HBCIs, fNIRS, ФМРТ, ЭЭГ, ЭМГ, МЭГ.

Для цитирования: Самандари А.М. Спектроскопия в околоинфракрасном диапазоне (fNIRS) как гибридная система: обзор. *Моделирование, оптимизация и информационные технологии.* 2024;12(1). URL: https://moitvivt.ru/ru/journal/pdf?id=1459 DOI: 10.26102/2310-6018/2024.44.1.005 (на англ.).

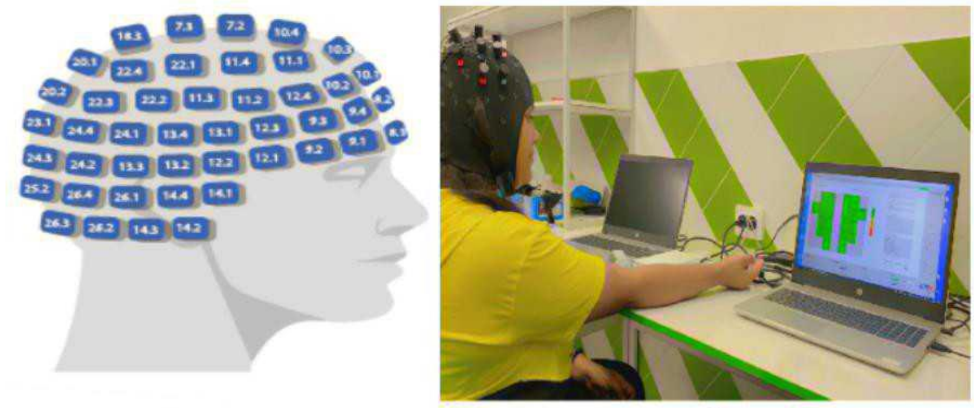
Introduction

Scientific history has demonstrated that no technical tool has continuous endurance; its work may end or be followed by sophisticated sequences to keep up with scientific modernity. Recently, medical imaging technologies have begun to appear in various fields, especially in medicine. The variety of medical imaging techniques aims at the accurate study of all organs and components of the body with the view to diagnosing the affected organ or component and treating, activating, or rehabilitating it as required by the need of that organ and with greater benefit: the focus of neuroimaging techniques is the study of brain activity. Note that these medical imaging techniques are not limited to a single scientific concept. In addition, they fall within a multidisciplinary concept. For example, neural interfaces and their development are closely related to the concept of linear physics [1], and the concept of medical imaging technologies is related to biological concepts, engineering, and artificial intelligence.

At the intersection of sciences, medical imaging techniques, especially functional near-infrared spectroscopy technique (fNIRS), are the obvious example that intersects these sciences according to the concept of BCI (brain computer interfaces). Using neuroimaging methods such as electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and fNIRS based on BCI, which depends functionally on the real-time detection of characteristic wavelength or patterns of brain activity and dynamically on the transformation of the information obtained into control commands for external devices that have become commonly used, such as wheelchairs, prostheses, and others. Increasing the accuracy of the classification of BCI brain signal patterns is an ongoing challenge to create a perfect BCI.

This classification includes a high and acceptable accuracy when it is a standard for non-invasive BCI classifiers used for communication tasks, neurological rehabilitation or operator assessment, but it is clearly insufficient and requires more accuracy due to the sensitivity of their use to control external devices such as an artificial hand. Therefore, an important task is to improve the accuracy of processing brain signals in real time and, as a result, increase the accuracy in recognizing mental commands. This may be attributed to the creation of multimedia hybrid BCIs, or hybrid brain-computer interface systems (hereafter referred to as HBCIs) that use several types of signals. The unique distinguishing characteristics of HBCIs is to take advantage of different technologies, and this is what makes them widely used with hybrid technologies as well and can be called this system (hybrid based on hybrid).

Recent scientific research has proven that the HBCIs application does not depend on two hybrid technologies only in terms of operation, but also extends to different hybrid technologies such as EEG-fNIRS [2] and EEG-EMG [3] and does not depend in terms of application on a specific software, but also extends to the comprehensiveness of its application in wide and different fields as controlling the movement of robots, detecting and preventing brain diseases, monitoring and controlling normal and pathological cognitive activity and others. EEG is non-invasive based on electrical activity of the nervous system still very low for the exchange of information between the brain and the machine. EEG technology has proven its presence in many fields, but in the field of its use in controlling artificial limbs it has not found application because of its disadvantages in this field. Like the context of this fNIRS which is a non-invasive neuroimaging technique based on chemical processes activity, due to its advantages that compensate for the disadvantages of EEG, they may form a hybrid system for artificial control. Among the various possible HBCIs, the hybrid EEG-fNIRS based is the most studied because of the complementary characteristics of EEG and fNIRS. In terms of classification accuracy and information transfer rate HBCIs could achieve a better overall performance compared with unimodal BCIs [2]. MEG is a noninvasive method of brain imaging and provides signals with higher spatiotemporal resolution, which is not present in fNIRS. It covers the entire cerebral cortex (MEG) (Figure 1, a) enables recording events for up to milliseconds as well as determining the sources of the magnetic field in the cerebral cortex with high accuracy [4]. fNIRS is located above the frontal lobe area of the brain with a noticeable delay period for recording events (Figure 1, b). By integrating MEG and fNIRS and based on the additional benefits they provide, higher spatial and temporal resolution can be provided than any other method [5]. This is because the hybrid system between the fNIRS and the MEG is better to use than to use it independently.



a b

Figure 1 – It is shown how (a) the entire cerebral cortex (MEG) and (b) the frontal lobe area (fNIRS) are covered
Рисунок 1– Показано, как покрывается (а) вся кора головного мозга (МЭГ) и (б) область лобных долей (fNIRS)

In the scientific literature focusing on surface electromyography (sEMG) which records the electrical activity represented by muscle dynamics for action potentials that initiate muscle contraction and force production and fNIRS, researchers have explored a variety of topics related to physiological measurement techniques, where there were positive correlations between EMG signals and fNIRS in all participants (Figure 2) [6].

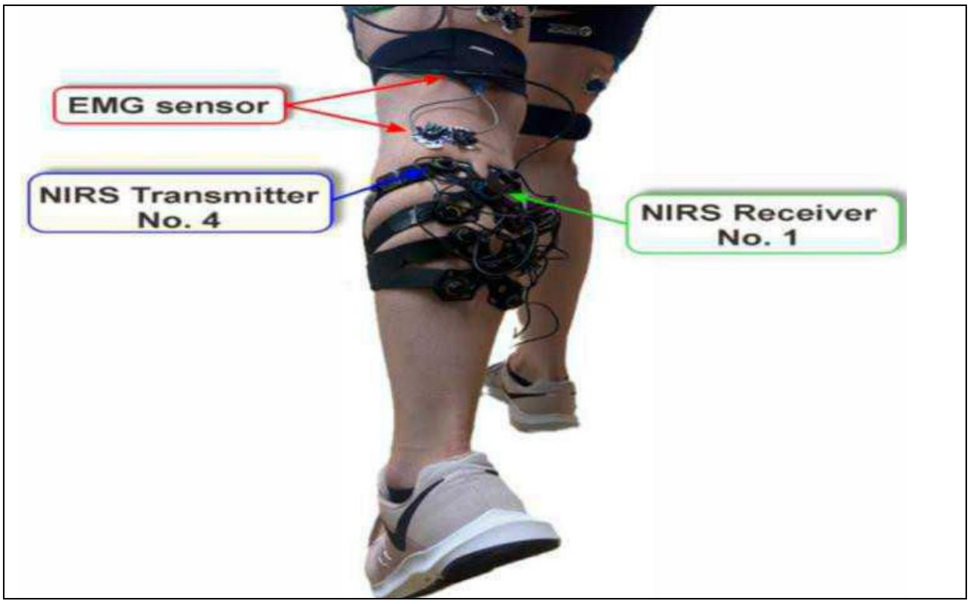


Figure 2 – EMG and fNIRS sensors are installed on the patient's body to measure such parameters as oxygen consumption and muscle activation
Рисунок 2 – ЭМГ и fNIRS датчики устанавливаются на тело пациента для измерения таких параметров, как потребление кислорода и мышечная активность

fNIRS and fMRI are based on the principle (blood-oxygenation-level-dependent) which (hereafter referred to as BOLD). Despite the fact that fNIRS and fMRI measure essentially the same activity, in different approaches, fMRI uses the different magnetic properties of HbO and HbR , while fNIRS uses the different optical properties of HBO and HbR (which absorb near-infrared light at different frequencies [7, 8]. Activating motor imagery should lead to increased coordination of oxygenation of the blood, thus creating doubt in the reliability of fNIRS for BCI applications [9].

fNIRS provides a cost-effective and portable alternative to fMRI to assess cortical activity changes based on circulatory signals. The spatial and temporal bases of the fMRI signal and the concentration of fNIRS corresponding to the chromophore measurements are still not completely clear. Fingerprinting of the brain indicates proven success with fMRI, whereas the results of experimental studies using fNIRS show depending on the number of runs and brain regions used for classification with an average classification accuracy ranging from 75 % to 98 %. Under the right conditions, brain fingerprinting with fNIRS is close to 99,9 % accuracy found with fMRI [10]. While in assessment of the spatial correspondence between fNIRS and fMRI hemodynamic responses in motor tasks, no statistically significant differences were observed in the multimodal spatial correspondence between HbO, HbR, and HbT for motor tasks. A hybrid approach to modeling fMRI data using their corresponding fMRI measurements (HBO, HPR, and HbT) from acquired asynchronously, would help to identify the corresponding active groups of motor-related areas [7]. That is, fNIRS models will continue to benefit from systematic verification by fMRI, especially if they target a specific cortical area [11]. The approach of fNIRS due to its being portable, wearable and high intensity combined and diffuse optical tomography can be an important approach that can open new areas of neurology by enabling functional neuroimaging of the human cortex with a resolution comparable to fMRI in almost any environment and population [12]. fMRI is the gold standard for modern functional neuroimaging, and despite its essential use in cognitive neuroscience and clinical research, its disadvantages support the idea of using it as a technical combination with fNIRS.

Numerous studies have shown that there is a growing trend and the possibility of their use to complement each other when the use of fMRI appears likely because there is a risk of using it independently [7]. In view of the shortcomings inherent in the above-mentioned technologies, this review aims to point out fNIRS as a reliable technology for the formation of a hybrid system for recording, analyzing and monitoring brain activity to perform various tasks such as controlling the movement of prostheses, detecting brain diseases and monitoring psychophysiological states, monitoringnormal and pathological cognitive activity and etc.

Materials and Methods

The purpose of this review is to explore the feasibility of fNIRS and its use as a hybrid system with other medical technologies, particularly EEG and EMG. In addition, the relationship between fNIRS with other technologies, such as MEG, fMRI, and diffuse optical tomography technologies that related to the subject of the review, whether it is used as a stand-alone system or as a hybrid system. This has been done by analyzing scientific articles, master's theses, and recent doctoral dissertations limited to the four years from 2020 to 2023.

We took upon ourselves the diversity of searching for sources that are strongly related to our topic in reliable databases we searched in databases, namely, domain, Google Scholar, and various other sites such as the first site https://scholar.google.com/ and others. In addition, various links are indicated as https://www.mdpi.com/journal/sensors, https://www.refseek.com and others, which are listed as reliable references at the end of the literature review. The search direction centered on the keywords: HBCIs, fNIRS, fMRI, EEG and EMG. Finally, the relevant articles were reviewed. The recommendations of experienced people and their comments were considered by deleting and adding systematic reviews and targeted analysis.

HBCIs

Understanding brain functions is essential for efficient BCI applications, and its development is closely related to physics. The classification of brain states can be performed in real time in accordance with the registered brain activity caused either by spontaneous physiological processes or by external stimulation using an intelligent BCI system. BCIs are usually divided into categories of unidirectional (receiving signals from the brain or sending them to it) and bidirectional (allowing information to be exchanged in both directions), and this depends on the direction of their work [13]. The classification of BCIs in general is given below [1, 14].

Control command-based classification

According to the type of control command given by the BCI operator, neural interfaces can be classified as follows:

1. **Active BCI** uses changes in brain activity, directly and consciously controlled by the operator of the neurointerface, regardless of external events, to receive control commands.

2. **Reactive BCI** detects and classifies the brain's response (for example, evoked potential) to external triggers (visual, auditory, tactile, etc.) for control commands.

3. **Passive BCI** analyzes the user's current brain activity without any targeted monitoring to obtain information about the actual state of the brain, for example, attention, switching activity, emotional state, etc. As a task for raising hands to study possible cerebral hemodynamics, the trigger is passive action [15].

Input data processing modality-based classification

The classification here is based on synchronization of the input data processing modality, BCI can be classified as follows:

1. Synchronous BCI specializes in analyzing brain signals only during predefined time intervals, whereas any brain signals are outside the pre-set time periods, they will be ignored.

Thus, the operator can create commands only during certain periods of time determined by synchronous. In fact, synchronous systems are reactive although they can also be passive.

2. Asynchronous BCI on the contrary, here the monitoring is continuously the signals of the brain, regardless of the time the operator acts. Therefore, asynchronous BCI provides a more natural human-machine interaction than synchronous BCI. However, asynchronous BCIs are more complex and require large computational costs. Active and passive BCIs are usually asynchronous [16].

Invasive and noninvasive BCI and Brain-machine interfaces

The classification based on the type of electrophysiological recordings depending on their invasivity can be classified as:

1. **Noninvasive BCI** limited to recording brain activity of the surface area of the head. This approach has proven useful in helping patients develop and provide limited bandwidth communication channels with the outside world.

2. **Invasive BCI** records brain activity intracranially using implanted electrodes.

And the above, the HBCIs are not limited to single data processing, but are based on hybrid double and triple data processing, and this is what makes the HBCIs [9, 16, 17, 18]. The main challenges of HBCIs is the control of prostheses or external devices in general by the electrical activity of the brain as EEG [19] or by the chemical activity as fNIRS [20], whether used individually or in a hybrid way [21]. A large percentage of the BCI system uses only one type of physiological signal, while the HBCIs, which take the advantages of different techniques, take two phases of the HBCIs, which combine active and passive neuron interfaces, as shown in Figure 3 [1].

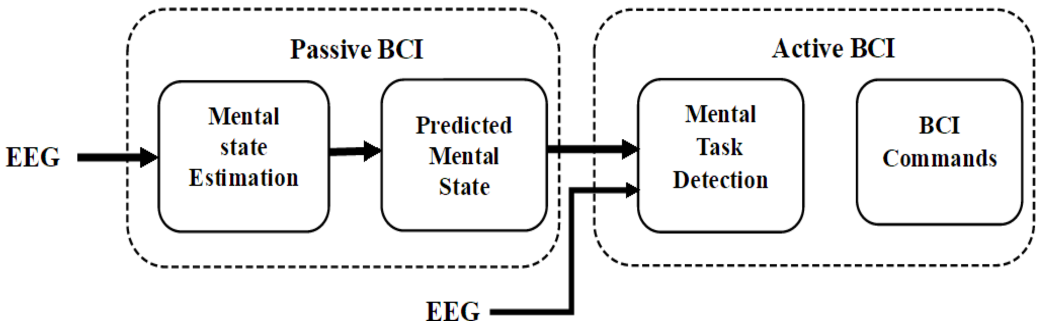


Figure 3 – Hybrid active-passive BCIs

Рисунок 3 – Гибридные активные–пассивные BCI

HBCIs of active and passive are more effective, enable estimation of the operator's mental state, and take advantages of different techniques such as fNIRS and EEG [17, 22, 23] and takes advantages of hybrid technologies EEG-EMG [24]. In the context of a hybridization system, a HBCIs can be in three types according to various signals of brain activity:

1. **HBCIs** when various reflected signals of brain activity are used.

2. **HBCIs** when signals of brain activity in conjunction with external signals of different nature are used.

3. **HBCIs** when various physiological brain activity simultaneously with recording technology are used.

It has been confirmed that the performance of individual BCI provides a lower classification accuracy than HBCIs. In a related context, one of the main reasons why HBCIs are not widely used is the enormity of their hardware and complexity. To decode this complexity, it is necessary to implement lightweight and compact HBCIs with care to reduce performance degradation. On this track, experimental studies have shown that the use of HBCIs with only 2 channels of EEG method and 2 pairs (sources-detectors) of fNIRS can achieve high classification accuracy, while the system is characterized by ease of use [2].

Hybrid fNIRS and EEG

The main essence of the hybrid system configuration of any system, whether it is a plant, animal, technical, or software system, is that one of the systems must complement the shortcomings of the other, noting that the hybrid system configuration must be conditioned to achieve outputs that are not equal to those received from the autonomous system, but the results must be clearly superior when using the hybrid system. On the other hand, when proceeding to the formation of a hybrid system, it should be if there are at least partially similar characteristics in both systems, which allows us to simply form a hybrid system.

The possibility of configuring a hybrid system of fNIRS and EEG is consistent with the above, because the outcomes that obtained from these techniques are better than those obtained when used independently, and some characteristics of these two techniques are similar. In the composition of EEG, sensors-electrodes are placed on the skin of the upper part of the skull (international system "10-20") and capture electrical signals from neurons in the brain. This can be measured in the electrical activity of the brain, can monitor complex neuronal activity and its changes [1].

EEG has many advantages and disadvantages that may be compatible with fNIRS. For example, they are compatible with non-surgical intervention, EEG technology may be affected by its very high sensitivity to artifacts; therefore, fNIRS may become an alternative to this feature, or there may be a challenge facing the hybrid system involving these two technologies. In addition, the EEG signals provide high temporal resolution, allowing real-time measurement of motor imagery [4], which can be converted into control signals to assist with motor movements. Unlike fNIRS, which suffers from a time delay of 3–5 seconds in detecting areas of brain activity. It has also been widely reported that better BCI performance can be achieved with multimodal analysis instead of standalone EEG signals. Therefore, multimodal studies that assess both the electrical activity of the brain as well as the activity of the circulatory system attracted great attention of researchers [25, 26]. Moreover, recent scientific studies based on the analysis of activated brain regions using fNIRS proved that the auxiliary motor cortex was obviously activated during motor imagery, which means that hybrid signaling with a hybridization strategy can enhance stability and error ignoring in BCI systems, which qualifies it to be a valuable technique for practical applications, as shown in Table 1 [27].

Table 1 – Comparison of single-use or hybrid scientific research of fNIRS technology from 2020 to 2023
Таблица 1 – Сравнение одноразовых или гибридных научных исследований технологии fNIRS с 2020 по 2023 гг.

Ref.	Year	System/alone or hybrid	Method	Accuracy or mean accuracy, %
[28]	2020	EEG	Double constrained nonnegative matrix factorization (DCNMF)	79,00
[29]	2021	EEG	End-to-end shallow architecture	83,20

Table 1 (extended)
Таблица 1 (продолжение)

Ref.	Year	System/alone or hybrid	Method	Accuracy or mean accuracy, %
[30]	2022	EEG	Manifold embedded transfer learning (METL)	83,14
[31]	2020	fNIRS	Stepwise regression analysis based on sequential feature selection (SWR-SFS) and ReliefF methods	78,27 HbR 77,41 HbO
[32]	2020	fNIRS	Signal Mean (SM), Skewness (SK), Kurtosis (KR), Standard Deviation(SD), Signal Peak (SP), and Signal Variance (SV)+KNN	90,54
[33]	2020	fNIRS	CSP+LSVM	71,4
[34]	2021	fNIRS	NN_LSTM, NN_ConvLST, NN_ResNet	91
[35]	2020	EEG+fNIRS	Pearson correlation coefficient-based feature selection (PCCFS)	79,31
[36]	2022	EEG+fNIRS	Vector-phase analysis (VPA)	82, 89, 87, 86
[37]	2022	EEG+fNIRS	fNIRS-guided attention network (FGANet)	78,59 ± 8,86
[27]	2023	EEG+fNIRS	FBCSP+PCA+SVM, GLM+MBLL	92,25 ± 4,99

These results demonstrate that hybrid signals with a combined strategy can enhance the stability and fault tolerance in BCI systems, which makes them valuable for scientific and practical applications. Despite the availability of multiple recording methods, the combination of EEG-fNIRS carries a clear signal as a promising approach and this is related to low cost, flexibility in portability, low interference, and good spatial and temporal resolution [21, 38]. In brief, the conclusion is that EEG and fNIRS, the recording of each of which provides additional information about the bioelectric activity of the brain. In addition, the combination of these two technologies has certain unique characteristics, as the rationale behind their combination is their dependence on a physiological phenomenon called neurovascular coupling [39] within the brain, which makes them more useful in certain applications. The combination of these two technologies may be the most promising system for controlling prostheses [40, 41].Nevertheless, fNIRS technology can be considered as the only possible alternative to EEG or form with it a hybrid system for creating systems for recording brain activity in a mobile portable BCI in the near future.

Hybrid fNIRS and EMG

Electromyography (EMG) is a diagnostic method that enables the recording of the electrical activity of bioelectric signals resulting from the activities of the skeletal muscles. Surface electromyography (sEMG) measures the electrical signal on the skin’s surface, which is generated by skeletal muscles (Figure 4). It is often performed while stimulating the relevant motor and peripheral nerves. The measurement may be performed either in an invasive or surface (noninvasive) at the level of a single muscle fiber, single motor unit, or the entire muscle [42].

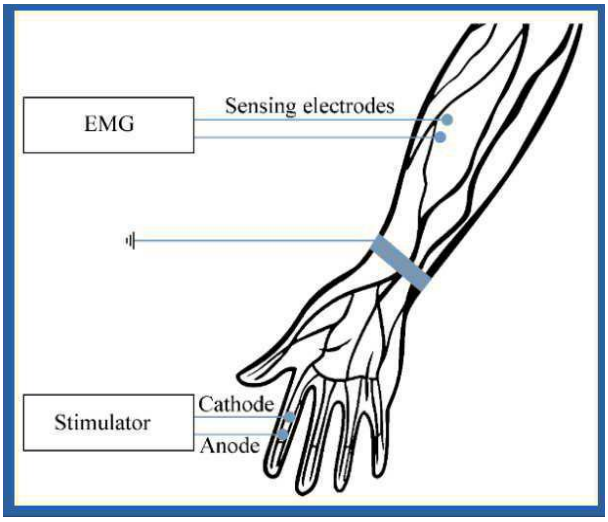


Figure 4 – Example of surface EMG signal measurement
Рисунок 4 – Пример измерения поверхностного ЭМГ-сигнала

The processing of information from the EMG enables diagnostics of muscle and neuromuscular disorders, or to analyze or use the sEMG for rehabilitation or robot control [43, 44]. The EMG frequency ranges vary from 0,01 to 10 kHz, depending on the type of examination (EMG or sEMG). The most useful and important frequency ranges are within the range of 50–150 Hz [42]. While the fNIRS frequency is approximately equal to 1 Hz at 830 nm, which is the optimal wavelength [1, 45]. The sEMG and fNIRS methods can be used separately or together. In scientific studies related to sports activity and neurophysiology, the focus has been on various sports disciplines as subjects of research [46] or the use of fNIRS as a hybrid system use it as a hybrid system with fNIRS to enhance the accuracy of classification of transuterine prostheses [47]. Several scientific studies have focused on the implementation of fNIRS and EMG technologies in motion but were not related to the interrelationship of signals during specific sports in dynamic movements. Moreover, most of them do not include a description of the signal analysis methods. Kimoto et al. found it possible to perform simultaneous EMG, mechanomyography (MMG) and near-infrared spectroscopy (NIRS) measurements at a local position using a wireless multi-layered sensor, which could be used to predict muscular fatigue [48]. Di Giminiani [49] when comparing regional muscle oxyhemoglobin saturation and surface EMG data measured under resting and dynamic conditions (treadmill run and strength exercises). They implemented a recently developed integrated quadriceps muscle oximetry/EMG system. When recording oxygen consumption and muscle activity of the gastrocnemius muscle of the left leg for participants. Daniel N. et al. found positive correlations between EMG and fNIRS signals, where the signal correlations between the participants with the most active and least active life style [6]. In a related context, the shapes of the changes in the EMG and fNIRS signals during exercise suggest a mutual relationship during dynamic movements. The close and significant positive correlations between cerebral oxygenation changes (fNIRS) and EMG signals during motor tasks provide evidence for creation hybrid system used to further explore the mapping relationship between brain activity and motor task execution and can be directed toward clinical studies.

Hybrid system from the signal acquisition stage to the application

To obtain the signal, the activation triggers of the motor cortex vary depending on the nature of the action. It was found that all etiologies of the motor cortex under different names cause a change in the concentration of hemoglobin, depending on which stimulus caused the activation of the cerebral cortex. When the event concerns rehabilitation and prosthetics, the triggers for the activation of the motor cortex should be movement stimuli. Triggers for activation of the motor cortex of the brain sound triggers may cause a change in hemoglobin concentration slower than the event-related potential; however, they capture the neural activity underlying the speech production processes , and this indicates the success of using fNIRS to study speech production [50-53] means that sound triggers activate the motor cortex of the brain [54]. In a related context that the state of signal gain at the work of medical imaging techniques based on BCI independently and the accompanying different stages from the signal acquisition stage, signal preprocessing, feature extraction, feature fusion, to the classification stage and then the application in the real world, the work of the hybrid system goes through the same stages as in Figure 5.

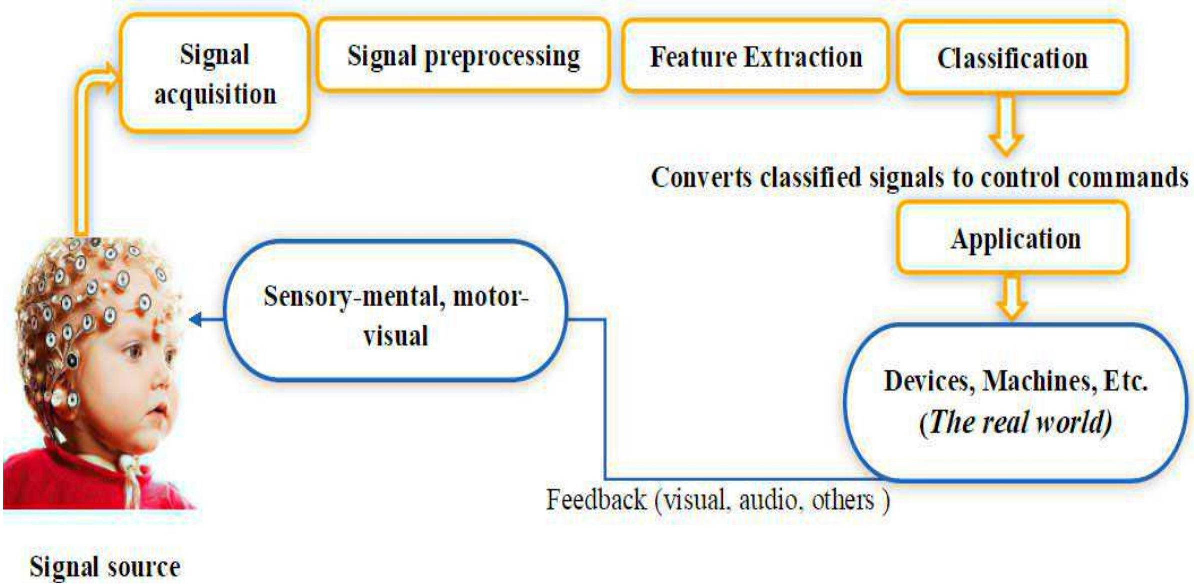


Figure 5 – fNIRS signal circuit as an individual system or as a hybrid system, comprises five steps of the BCI system
Рисунок 5 – Сигнальная схема fNIRS как отдельная система или как гибридная система включает в себя пять этапов системы BCI

The feature extraction process is not without challenges because it is dependent in high percentage on prior complex knowledge in time, and this leads to the risk of information loss [55]. There are different and popular ways of feature extraction. Brain signals can be filtered into three bands as EEG or filtered into one band as fNIRS to improve the signal quality for subsequent analysis [27]. Decreased number of extracted features and reduced computational complexity can be achieved by combining nonlinear feature extraction with stacking ensemble learning technique and genetic optimization for EEG-fNIRS based HBCI systems. The language of hybridization is not limited only to medical technologies such as fNIRS with other techniques, it can extend to any stage,from obtaining a biological signal to practical application. The combination consisting of wavelet packet decomposition with canonical correlation analysis for motion artifact correction from single-channel EEG and fNIRS signals is better than using wavelet packet decomposition independently [25]. In order to demonstrate the performance advantage of single-method and mixed methods by using the conventionalwhale optimization algorithm and binary enhanced whale optimization algorithm demonstrated a high classification accuracy (90.37 ± 7.66 % and 94.22 ± 5.39 %, respectively). The classification performance exhibited a 3,85 % increase compared with the conventional whale optimization algorithm [56, 57].

If technological progress is employed by the development of modern algorithms that will reduce by a high percentage the motion artifacts of the EEG and fNIRS data, and this is obviously extremely important for the interpretation of signals and the correct diagnosis and treatment by a medical doctor for all applications based on BCI. fNIRS improves spatial resolution, cortical sensitivity, and quantification by anatomical recording, and this requires the development of algorithms. After the brain signal is acquired by hybrid methods, it must be processed using one of the analysis processors. Perhaps the most used is principle component analysis or general linear model, which uses to analyze human neuroimaging data from both fMRI and fNIRS for the purpose of a non-verbal working memory task [7, 27, 40, 58]. After extracting features from fNIRS data, the classifier (as support vector machine) is necessary for the assignment of features, the identification of categories of motor activity (patterns), and then for the stage of practical application. This is the goal and success of each scientific experiment to crown it with practical application to reality. The continuous development of fNIRS along with machine learning algorithmscan significantly expand the implementation of fNIRS as a hybrid system for monitoring at the clinical level and facilitate the general interpretation of brain signals [59]. The information carried by the acquired EEG signals is shown in Figure 6 (A), while the biomarkers in the acquired fNIRS signal included the hemodynamic parameters which are (HBO), (HbR), and total-(HbT) hemoglobin, and the tissue oxygen saturation (SO2) shown in Figure 6 (B). The acquired signal of sEMG is the trainof the motor-unit action potentials generated by the muscle fibers of the motor unit in response to nervous stimulation and can be analyzed in both time and frequencydomains. Some common applications are shown in Figure 6 (C).

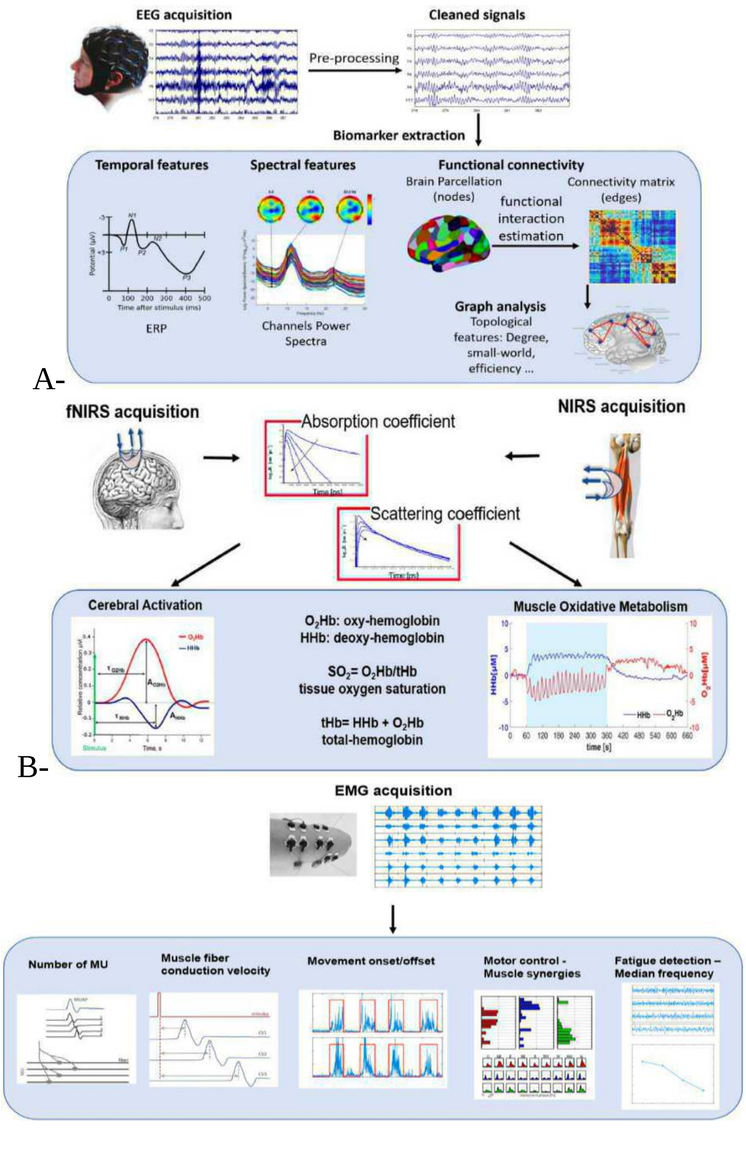


Figure 6 – Schematic representation of (a) EEG signal processing, (b) fNIRS and NIRS signal processing, and (c) EMG signal processing workflow and workflow and biomarkers [60]
Рисунок 6 – Схематическое представление (а) обработки сигналов ЭЭГ, (б) обработки сигналов fNIRS и NIRS и (в) обработки сигналов ЭМГ, а также рабочего процесса и биомаркеров [60]

Current and expected applications of hybrid systems

Technological systems such as EEG, sMEG and fNIRS contribute to their numerous uses independently in many areas such as movements, neurorehabilitation, neuroprosthetics etc, and this exists and is realistically tangible. Hybrid systems formed from a combination of these technologies that are superior that are superior on the individual system, as confirmed by scientific studies, will have the same applications as individual systems, but should be better, and this is the logic of hybrid system configuration.

A hybrid EEG-NIRS system combined with body motion capture allowed us to distinguish Parkinson’s disease with more than 83 % accuracy for each individual [61], and more recently to monitor non-responding patients with acute brain injury, obtaining 99 % accuracy in distinguishing patients that subsequently failed to recover recover consciousness [62]. The combination of EEG and fNIRS moreover, provides a useful approach for evaluating guided robot-assisted rehabilitation. For example, Wang et al. found that BCI-based neurofeedback training in chronic stroke increased their EEG event-related synchronization/desynchronization during motor imagery and enhanced cortical activity measured with fNIRS [60, 63].

The expected and recommended applications of EEG-fNIRS are the assessment of the development of mental fatigue during flight simulation [64], and EEG technology is still the leader in this field. The sEMG and fNIRS methods are used together to allow continuous monitoring of a muscle during motor activity or rehabilitative exercises [6]. The feasibility of fusing sEMG and fNIRS signals has been demonstrated to improve motion classification accuracy for elbow amputees [47], enhancing the control performances of multifunctional myoelectric prostheses in clinical application [65].

In brief, hybrid systems can play their role in many fields, including:

a) control of robotic devices, including exoskeletons, to increase human capabilities;

b) because of its ability to transmit information, it can provide social interactions by allowing social applications to accurately assess and transmit a person’s emotions, and this leads to improvement of self-control and psychophysiological state quality;

c) analysis and training of human resistance to specific stress effects;

d) revealing and preventing brain pathologies;

e) assessing and controlling psychophysiological states;

f) rehabilitation of people after brain damage, for example, restoration of motor skills after a stroke.

Conclusion

Comparing hybrid systems (fNIRS plus another technical tool) with the analysis of modern systematic scientific studies, can say that the hybrid system achieves an advantage better than individual use, such as fNIRS with EEG, where the results of classification accuracy showed their superiority over individual uses of both technologies. This is confirmation that the hybridization of these two technologies may be a promising hybrid system of prosthesis control. fNIRS has the ability to measure hemodynamics and enable cortical tissues where there is no danger and no restrictions in movement mobility, in addition to its advantages that offset the disadvantages of other medical imaging technologies, can be a hybrid mode that is superior in performance to that technology when used independently. The improvement of the accuracy of signal classification from low to high is a good indicator and another confirmation that hybrid technologies are the most promising candidate technology for scientific and practical applications. The presence of positive correlations between cerebral oxygen changes and EMG signals during motor tasks supports the idea of creating a hybrid system between EMG and fNIRS.

Despite this, there are hundreds of studies on our topic and successes found in some hybrid systems and failures in others. The focus should be on future studies involving the study of hybrid systems that have met with success to ensure their implementation in the real world (for each subject prepared for the study according to a system (hybrid based on BCI or HBCIs). As well as focusing on those that did not achieve success. This should not create obstacles for future investigations using fNIRS alone. For the upcoming future research and after proving that hybrid systems are superior on the individual system, questions and challenges come in which hybrid systems such as fNIRS+EEG or fNIRS+EMG will be the most promising and proven technology to be used for treating a disease and disabilities, or the individual system that is still in the research circle will be the leader in diagnosis and treatment if modern applied sciences can add their fingerprints to solve the challenges and disadvantages facing each system.

REFERENCES

1. Hramov A.E., Maksimenko V.A., Pisarchik A.N. Physical principles of brain–computer interfaces and their applications for rehabilitation, robotics and control of human brain states. *Physics Reports*. 2021;918:1–133. DOI: 10.1016/j.physrep.2021.03.002.
2. Kwon J., Shin J., Im C.H. Toward a compact hybrid brain-computer interface (BCI): Performance evaluation of multi-class hybrid EEG-fNIRS BCIs with limited number of channels. *PLoS One*. 2020;15:3. DOI: 10.1371/journal.pone.0230491.
3. Tyatyushkina O.Y., Ulyanov S.V. «Brain – Computer» interface (BCI). Pt I: Classical technology. *Systemanalysis in science and education*. 2023;(2):62–96. EDN: HNAGLM. URL: https://sanse.ru/index.php/sanse/article/view/581.
4. Lin J.F.L. Dual-MEG interbrain synchronization during turn-taking verbal interactions between mothers and children. *Cerebral Cortex*. 2023;33(7):4116–4134. DOI: 10.1093/cercor/bhac330.
5. Berestov R.M., Bobkov E.A., Belov V.S., Nevedin A.V. Brain-computer interface technologies for monitoring and control of bionic systems. *Journal of Physics: Conference Series*. 2021;46(4):924–927. DOI: 10.1364/OL.418284.
6. Daniel N., Sybilski K., Kaczmarek W., Siemiaszko D., Małachowski J. Relationship between EMG and fNIRS during Dynamic Movements. *Sensors*. 2023;23(11). DOI: 10.3390/s23115004.
7. Pereira J., Direito B., Lührs M., Castelo-Branco M., Sousa T. Multimodal assessment of the spatial correspondence between fNIRS and fMRI hemodynamic responses in motor tasks. *Sci Rep*. 2023;13:1. DOI: 10.1038/s41598-023-29123-9.
8. Tsvetanov K.A., Henson R.N.A., Rowe J.B. Separating vascular and neuronal effects of age on fMRI BOLD signals: Neurovascular ageing. *Philosophical Transactions of the Royal Society B: Biological Sciences*. 2021;376:1815. DOI: 10.1098/rstb.2019.0631.
9. Androu A., Daniel M., David J.C., Udunna A., Tracy S., Mamadou D., Adrian M.O., Keith S.L. Using fMRI to investigate the potential cause of inverse oxygenation reported in fNIRS studies of motor imagery. *Neurosci Lett*. 2020;714:134607. DOI: 10.1016/j.neulet.2019.134607.
10. Sergio L.N., Alex C.C., Forti R.M., Fernado C., Clarissa L.Y., Rickson C.M. Revealing the spatiotemporal requirements for accurate subject identification with resting-state functional connectivity: a simultaneous fNIRS-fMRI study. *Neurophotonics*. 2023;10(1). DOI: 10.1117/1.NPh.10.1.013510.
11. Klein F.S., Debener K.W., Kranczioch C. fMRI-based validation of continuous-wave fNIRS of supplementary motor area activation during motor execution and motor imagery. *Sci Rep*. 2022;12(1). DOI: 10.1038/s41598-022-06519-7.
12. Deligani R.J., Borgheai S.B., McLinden J., Shahriari Y. Multimodal fusion of EEG-fNIRS: a mutual information-based hybrid classification framework. *Biomed Opt Express*. 2021;12(3):1635. DOI: 10.1364/boe.413666.
13. Asanza V., Pelaez E., Loayza F., Lorente-Leyva L.L. Peluffo-Ordonez D.H. Identification of lower-limb motor tasks via brain-computer interfaces: a topical overview. *Sensors*. 2022;22(5). DOI: 10.3390/s22052028.
14. Janis P., Dmytro M. State-of-the-art on brain-computer interface technology. *Sensors*. 2023;23(13). *Multidisciplinary Digital Publishing Institute (MDPI)*. DOI: 10.3390/s23136001.
15. Lacerenza M., Frabasile L., Buttafava M., Spinelli L., Bassani E., Micheloni F., Amendola C., Torricelli A., Contini D. Motor cortex hemodynamic response to goal-oriented and non-goal-oriented tasks in healthy subjects. *Front Neurosci*. 2023;17: 1202705. DOI: 10.3389/fnins.2023.1202705.

16. Wang H., Yan F., Xu T., Yin H., Chen P., Yue H., Chen C., Zhang H., X, L., He Y., et al. Brain-controlled wheelchair review: from wet electrode to dry electrode, from single modal to hybrid modal, from synchronous to asynchronous. *IEEE Access*. 2021;9:55920–55938. DOI: 10.1109/ACCESS.2021.3071599.
17. Xu B., Li W., Liu, D., Zhang K., Miao M., Xu G., Song A. Continuous hybrid BCI control for robotic arm using noninvasive electroencephalogram, computer vision, and eye tracking. *Mathematics*. 2022;10(4):618. DOI: 10.3390/math10040618.
18. Sun Z., Huan Z., Duan F., Liu Y. A novel multimodal approach for hybrid brain-computer interface. *IEEE Access*. 2020;8:89909–89918. DOI: 10.1109/ACCESS.2020.2994226.
19. Wilson H., Golbabaee M., Proulx M.J., Charles S., Neill E.O. EEG-based BCI dataset of semantic concepts for imagination and perception tasks. *Sci Data*. 2023;10(1). DOI: 10.1038/s41597-023-02287-9.
20. Juanning S., Yi Y., Long X., Tianshuai X., Hao L., Yujin Z., Rixing J., Jinglian L., Dongdong W., Sijin W., Jianghong H. Evaluation of residual cognition in patients with disorders of consciousness based on functional near-infrared spectroscopy. *Neurophotonics*. 2023;10(2):025003. DOI: 10.1117/1.nph.10.2.025003.
21. Hasan M.A.H., Khan M.U., Mishra D. A computationally efficient method for hybrid EEG-fNIRS BCI based on the Pearson correlation. *Biomed Res Int*. 2020. DOI: 10.1155/2020/1838140.
22. Sial M.B., Wang S., Wang X., Wyrwa J., Ali S. A survey on EEG-fNIRS based non-invasive hBCIs. In: *2021 International Conference on Artificial Intelligence (ICAI), Islamabad, Pakistan, 2021*. p. 240–245. DOI: 10.1109/ICAI52203.2021.9445246.
23. Ailsworth J. *Development of neurofeedback therapies for hand rehabilitation in stroke.* PhD Thesis. North Carolina State University; 2023.
24. Lubo F., Haoyang L., Hongfei J. EEG-EMG analysis method in hybrid brain computer interface for hand rehabilitation training. *Computing and Informatics*. 2023;42:741–761. DOI: 10.31577/cai_2023_3_741.
25. Asmaa M., Saeed M.Q., Salankar N., Feng J., Ryszard T., Paweł P., Ahmed A., Mohamed H. Hybrid EEG-fNIRS brain-computer interface based on the non-linear features extraction and stacking ensemble learning. *Biocybern Biomed Eng*. 2023;43(2):463–475. DOI: 10.1016/j.bbe.2023.05.001.
26. Liu Z., Shore J., Wang M., Yuan F., Buss A., Zhao X. A systematic review on hybrid EEG/fNIRS in brain-computer interface. *Biomed Signal Process Control*. 2021;68 102595.
27. Tao X., Zhengkang Z. Motor imagery decoding enhancement based on Hybrid EEG-fNIRS signals. *IEEE Access*. 2023;11:65277–65288. DOI: 10.1109/ACCESS.2023.3289709.
28. Su J., Yang Z., Yang W.Y., Sun W.S. Electroencephalogram classification in motor-imagery brain-computer interface applications based on double constraint nonnegative matrix factorization. *Physiol. Meas.* 2020;41(7):075007.
29. Hermosilla D.M., Codorni R.T., Codorni R.L., Baracaldo R.S., Zamora D.D. Rodriguez Y.L.A., Alvarez J.R.N. Shallow convolutional network excel for classifying motor imagery EEG in BCI Applications. *IEEE Access.* 2021;9:98275–98286. DOI: 10.1109/ACCESS.2021.3091399.
30. Cai Y., She Q., Ji J., Ma Y., ZhangBJ., Zhang Y. Motor imagery EEG decoding using manifold embedded transfer learning. *J. Neurosci. Methods*. 2022;370:109489.
31. Eda A.A. Subject-specific feature selection for near infrared spectroscopy based brain–computer interfaces. *Comput. Methods Programs Biomed*. 2020;195:105535.

32. Ghaffar M.S.B.A., Khan U.S., Naseer N., Rashid N., Tiwana M.I. Improved classification accuracy of four class FNIRS-BCI. In: *Proc.12th Int. Conf. Electron., Comput. Artif. Intell. (ECAI). Bucharest, Romania: IEEE, Jun. 2020*. p. 1–5.
33. Wang H.K., Kim I., Kim Y., Kim H., Kim D. Comparative analysis of NIRS-EEG motor imagery data using features from spatial, spectral and temporal domain. In: *Proc. 8th Int. Winter Conf. Brain-Comput. Interface (BCI), Feb. 2020*. p. 1–4.
34. Asadullaev R.R., Afonin A.N., Shchetinina E.S. Recognition of patterns of motor activity by a neural network based on continuous optical tomography fNIRS data. *Ekonomika. Informatica*. 2021:48(4):735–746. DOI: 10.52575/2687-0932-2021-48-4-735-746. (In Russ.).
35. Cicalese P.A., Li R., Ahmadi M.B., Wang C., Francis J.T., Selvaraj S., Schulz P.E., Zhang Y. An EEG-fNIRS hybridization technique in the four-class classification of Alzheimer's disease. *J. Neurosci. Methods*. 2020;336:108618.
36. Arshia A., Khan M.J., Kashif J., Hasan S., Saddaf R., Noman N., Khan T.I. Hemodynamic response detection using integrated EEG-fNIRS-VPA for BCI. *Computers, Materials and Continua*. 2021;70(1):535–555. DOI: 10.32604/cmc.2022.018318.
37. Kwak Y., Song W.J., Kim S.E. FGANet: fNIRS-guided attention network for hybrid EEG-fNIRS brain-computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2022;30:329–339. DOI: 10.1109/TNSRE.2022.3149899.
38. Abdalmalak A. *Detecting command-driven brain activity in patients with detecting command-driven brain activity in patients with disorders of consciousness using TR-fNIRS.* PhD thesis. The University of Western Ontario; 2020.
39. Jianeng L., Jiewei L., Zhilin S., Ningbo Y., Jianda H. An EEG-fNIRS neurovascular coupling analysis method to investigate cognitive-motor interference. *Computers in Biology and Medicine*. 2023;160:106968. DOI: 10.1016/j.compbiomed.2023.106968.
40. Li R., Yang D., Fang F., Hong K.S., Reiss A.L., Zhang Y. Concurrent fNIRS and EEG for brain function investigation: a systematic, methodology-focused review. *Sensors*. 2022;22(15). DOI: 10.3390/s22155865.
41. Ergün E., Aydemir Ö., Korkmaz O.E. A novel scrolling text reading paradigm for improving the performance of multiclass and hybrid brain computer interface systems. Available at SSRN: https://ssrn.com/abstract=4576653. DOI: 10.2139/ssrn.4576653.
42. Radek M., Martina L., Michaela S., Rene J., Khosrow B., Radana K., Aleksandra K.S. Advanced bioelectrical signal processing methods: Past, present, and future approach—part iii: Other biosignals. *Sensors*. 2021;21(18). DOI: 10.3390/s21186064.
43. Chunfu L., Ruite G., Zhichuan T., Xiaoyun F., Lekai Z., Keshuai Y., Xuan X. Multi-channel FES gait rehabilitation assistance system based on adaptive sEMG modulation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2023;31:3652–3663. DOI: 10.1109/tnsre.2023.3313617.
44. Song T., Yan Z., Guo S., Li Y., LiX., Xi F. Review of sEMG for robot control: Techniques and applications. *Applied Sciences (Switzerland)*. 2023;13(17). DOI: 10.3390/app13179546.
45. Cheng X., Sie E.J., Boas D.A., Marsili F. Choosing an optimal wavelength to detect brain activity in functional near-infrared spectroscopy. *Opt Lett*. 2021;46(4):924. DOI: 10.1364/ol.418284.
46. Taborri J., Keogh J., Kos A. et al. Sport biomechanics applications using inertial, force, and EMG sensors: a literature overview. *Appl Bionics Biomech*. 2020;2020:2041549. DOI: 10.1155/2020/2041549.
47. Neelum Y.S., Zareena K. et al. Enhancing classification accuracy of transhumeral

prosthesis: a hybrid sEMG and fNIRS approach. *IEEE Access*. 2021;9:113246–113257. DOI: 10.1109/ACCESS.2021.3099973.
48. Kimoto H.F., Machida M. A wireless multi-layered EMG/MMG/NIRS sensor for muscular activity evaluation. *Sensors*. 2023;23(3). DOI: 10.3390/s23031539.
49. Giminiani R.D., Marco C., Marco F., Valentina Q. Validation of fabric-based thigh-wearable EMG sensors and oximetry for monitoring quadricep activity during strength and endurance exercises. *Sensors*. 2020;17:1–13. DOI: 10.3390/s20174664.
50. Walczak E.J. Exploration of speech induced suppression using functional near-infrared spectroscopy (fNIRS). Bioarxiv [Preprint]. DOI: 10.1101/2023.03.05.531176.
51. Siepsiak M., Vrana S.R., Rynkiewicz A., Rosenthal M.Z., Dragan W.Ł. Does context matter in misophonia? A multi-method experimental investigation. *Front Neurosci*. 2023;16:880853. DOI: 10.3389/fnins.2022.880853.
52. Ma T., Chen W., Li X., Xia Y., Zhu X., He S. Fnirs signal classification based on deep learning in rock-paper-scissors imagery task. *Applied Sciences*. 2021;11(11). DOI: 10.3390/app11114922.
53. Sebastian H., Erica F., Charisse P., Judit G., Janet F.W., Laurel J.T., Brett B.F. Babies, bugs and brains: How the early microbiome associates with infant brain and behavior development. *PLoS One*. 2023;18(8). DOI: 10.1371/journal.pone.0288689.
54. Waight J.L., Arias N., Jiménez-García A.M., Martini M. From functional neuroimaging to neurostimulation: fNIRS devices as cognitive enhancers. *Behav Res Methods*. 2023. DOI: 10.3758/s13428-023-02144-y.
55. Zhang X., Yao L., Wang X., MonaghanJ., Mcalpine D., Zhang Y. A survey on deep learning-based non-invasive brain signals: recent advances and new frontiers. *J Neural Eng*. 2021;18(3). DOI: 10.1088/1741-2552/abc902.
56. Nadimi-Shahraki M.H., Zamani H., Mirjalili S. Enhanced whale optimization algorithm for medical feature selection: A COVID-19 case study. *Comput Biol Med*. 2022;148:105858. DOI: 10.1016/j.compbiomed.2022.105858.
57. Ali M.U., Kim K.S., Kallu K.D., Zafar A., Lee S.W. OptEF-BCI: an optimization-based hybrid EEG and fNIRS-brain computer interface. *Bioengineering*. 2023;10(5):608. DOI: 10.3390/bioengineering10050608.
58. Brekke F. *Non-verbal working memory: A functional near-infrared spectroscopy (fNIRS) and functional magnetic resonance imaging (fMRI) comparison*. Master's Thesis. University of Bergen; 2023.
59. Phillips V.Z., Canoy R.J., Paik S.H., Lee S.H., Kim B.M. Functional near-infrared spectroscopy as a personalized digital healthcare tool for brain monitoring. *Journal of Clinical Neurology*. 2023;19(2):115–124. DOI: 10.3988/jcn.2022.0406.
60. Alessandro S. et al. A narrative review on multi-domain instrumental approaches to evaluate neuromotor function in rehabilitation. *Healthcare*. 2023;11(16). DOI: 10.3390/healthcare11162282.
61. Mohammadreza A., Seyed B.B., Roohollah J., Nicholas C., Rassoul D., Yalda S., Kunal M. Merging fNIRS-EEG brain monitoring and body motion capture to distinguish Parkinsons disease. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2020;28(6):1246–1253. DOI: 10.1109/TNSRE.2020.2987888.
62. Marwan H.O., Mahasweta B., Kirsten M., Søren K., Johannes G., Jesper K., Anirban D., Daniel K. Resting-state NIRS–EEG in unresponsive patients with acute brain injury: a proof-of-concept study. *Neurocrit Care*. 2021;34(1):31–44. DOI: 10.1007/s12028-020-00971-x.
63. Zhongpeng W., Cong C., Long C., Bin G., Shuang L., Minpeng X., Feng H., Dong M. Multimodal neural response and effect assessment during a BCI-based neurofeedback training after stroke. *Front Neurosci*. 2022;16:2022. DOI: 10.3389/fnins.2022.884420.

64. Anneke H., Nils C. Assessing the development of mental fatigue during simulated flights with concurrent EEG-fNIRS measurement. *Sci Rep*. 2023;13(1). DOI: 10.1038/s41598-023-31264-w.
65. Xiaohan W., Zichong L., Mingxia Z., Weihua Z., Songyun X., Seng F.W., Huijing H., Le L. The interaction between changes of muscle activation and cortical network dynamics during isometric elbow contraction: a sEMG and fNIRS study. *Front Bioeng Biotechnol*. 2023;11:1176054. DOI: 10.3389/fbioe.2023.1176054.

ИНФОРМАЦИЯ ОБ АВТОРЕ / INFORMATION ABOUT THE AUTHOR

Самандари Али Мирдан, аспирант, Белгородский государственный национальный исследовательский университет, Белгород, Российская Федерация.
e-mail: aliofphysics777ali@gmail.com

Samandari Ali Mirdan, Postgraduate Student, Belgorod State National Research University, Belgorod, the Russian Federation.

Статья поступила в редакцию 14.10.2023; одобрена после рецензирования 20.12.2023; принята к публикации 19.01.2024.

The article was submitted 14.10.2023; approved after reviewing 20.12.2023; accepted for publication 19.01.2024.