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Data Processing in Brain Control Interface Application

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Abstract
Brain Computer Interface (BCI) is an innovation that help people with impairment to do their daily activities. BCI processed its data through several processes such as pre-processing, feature extraction, and classification. This review paper provide the process that mostly used by researchers.

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INTRODUCTION

Walking, jogging, and running are examples of daily activities among humans that required the brain to have complex coordination in the musculoskeletal system and the limb. However, people with severe injury or trauma may lose their ability to control their movements or speech. To help the survivors who already lose their abilities, over the years, researchers around the world had been trying to invent a communication channel using artificial connections that are based on the human brain in order to restore the function of paralyzed body parts [1].

Brain-Computer Interface (BCI) has become the bridge between the brain and the machine as the innovation that help the impaired person that cause by injury or trauma to do their daily activity [4]. The development of BCI techniques is growing rapidly these days, where it helps people to their daily activities become easier through communication or operating assistive device [5]. Brain-Computer Interface (BCI) is a communication system that translates the signals produced by brain activity into control signals without the involvement of peripheral nerves and muscles in the form of hardware and software muscles [2],[3].

In the late 1970s, the first research on BCI held by researchers using non-human subjects such as monkeys and rats through their studies and led them to find that cortical neurons can be used to control their neural actions [4], [5]. However, the research in the BCI area remains slow cause of the limited computer capabilities and knowledge about the physiology of the brain (Shih et al., 2012). As technology grows up, the development of BCI also growing up, whereas these technologies develop the scope of BCI research to Artificial intelligence (AI) [4]. The technology helped researchers to record the activity of the human brain, emotion recognition, human limb/hand movement detection, and many more [4]. The medical field is not the only main focus of BCI application, there are several fields that become the focus of the application of BCI such as gaming, entertainment, and experimental learning [4].

The purpose of this paper is to review and summarize the feature extraction, and classification methods that have been applied in BCI applications.

There are five steps to process the signals in the BCI application, which are signal acquisition, pre-processing, feature extraction, classification, and the application interface [6]. Signal acquisition is the first step where the signals are collected through numerous sensor modalities. In signal acquisition, the human brain signals are recorded then the recorded signals are executing the task by transmitting the signals to the machine [4]. Invasive and non-invasive are two steps of recording techniques in the BCI [6]. The invasive technique required surgery where the electrodes are implanted in the skull, however, the non-invasive technique is the opposite of the invasive where it is not required the surgery to implant the electrodes [6]. Among both techniques, the non-invasive is recommended due to the less time-consuming and does not require surgery [5],[6]. To record the signals, there are several tools that have been used such as functional magnetic resonance imaging (fMRI), Magnetoencephalography (MEG), electroencephalogram (EEG), and functional near-infrared spectroscopy (fNIRS).

Among the techniques above, EEG has become the most advantageous tool due to its portability, ease to use with a high temporal resolution, and inexpensive (Alzahab et al, 2021). Although EEG is popular, this tool, however, has poor spatial resolution and inherent sensitivity to motion artifacts which can affect the result (Mihajlović et al, 2014). To cope with the EEG limitation, fNIRS has become the solution where it can provide a good balance between spatial and temporal resolution (Ma et al, 2021). Besides, fNIRS is also its insensitivity to noise, low cost, and portability (Ma et al, 2021). Both EEG and fNIRS have become famous tools in BCI [7]. Combining them has also proven to give a higher performance (Sengupta et al, 2018, Ho et al, 2021). The combination of EEG and fNIRS in the BCI system has significantly increased throughout the years in medical treatment (Sengupta et al, 2018, Ho et al, 2021).

Functional near-infrared spectroscopy (fNIRS) is a famous tool among other neuroimaging methods for recording regional tissue oxygenation continuously [8]. Near-infrared light is used in the fNIRS to collect the signals by determining haemodynamic response from the oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) [9], [10]. In order to record the concentration of the blood, fNIRS used pars of near-infrared light emission of a detector with the range of amplitude region between 650-950 nm at two or more wavelengths. By radiating the red light of the near-infrared to the scalp, it caused multiple photon scattering and diffusing through the brain tissue. The absorbed and scattered photons that have returned to the surface are detected by optical fiber detection.

The different absorption spectra in fNIRS signals (i.e. HbO and HbR) lead the researchers to use modified Beer-Lambert Law (MBLL) [11]. MBLL converts the change of optical density into the change in concentration of HbO and HbR. The measurement of the changes in the hemoglobin is based on the theory of neurovascular coupling and optical spectroscopy [7]. According to the theory, the increase in the activities of the neural networks may cause an increase in oxygen consumption to achieve the needs for neuronal tissue. As a result, HbR increases when oxygen is consumed and causes a decrease in HbO.

Pre-processing is another step to use in order to remove the unwanted signals in the data caused by the noises during recording data. Then following by feature extraction to differentiate the characteristics of the relevant signal. After that, classification is applied to classify the signals by using machine learning applications (i.e. ANN, CNN). In the last step, classified signals produced the translated signals into instructions for a device such as a computer or assistive appliance.

METHOD

A. Pre-processing in BCI

Noises are the disturbance that is carried by the raw or unprocessed signals during acquisition. In fNIRS signals data, the noises originate from talking or movement of the face, head, and upperbudy during the recording which named as motion artifacts [8]. This type of noises have caused the displaced of optodes on the scalp and produced a sharp high-frequency displacement, slow wave drifts, or baseline shift in the fNIRS signal [8]. Another noises is blood flow changes that are irrelevant to neural activity [8]. The final result of the data irrelevant due to the noises that may created in the recording process. To solve the noises problem, pre-processing process is become an effective way to remove the unwanted noises in the signals data [21].

Filtering is one of the famous tool in pre-proceesing especially in the fNIRS BCI application [21]. This tool became famous among the researchers because of its ability to being quick and easy to process [21]. There are several steps that is implied to used this tools, the first one is by choosing the types of the filter that suitable for their research while preserving the functional hemodynamic signal. The selection of the filter order is the second step of this process, at this step the higher number of filter order that chosen by the researches may caused greater slope at the cut-off frequency. The last step of this process is choosing the suitable cutoff frequencies for the signals.

Several filters have been applied in fNIRS BCI application, such as low-pass and high-pass filters. The low-pass filter is a filter that used to attenuate the high-frequency signals which higher than the cutoff frequency numbers. High-frequency noises may affect by the environment such as extraneous light and physiological noise. Opposite side of low-pass filter, high-pass filter is used to remove low-frequency noise than the cutoff frequency numbers. Low-pass frequency noises may caused from gradual movements of the optodes on the scalp which may produced baseline drift.

Another type of filter named Band-pass filter is a popular and widely used filter in the fNIRS BCI application. A Band-pass filter is a combination filter between low-pass and high-pass filters that works by passing certain bands and attenuating the frequencies outside the band. There are several subtypes of bandpass filter which are Butterworth, Chebyshev type I and II, and the Elliptic filters [6][8]. Butterworth subtypes are the most used filter among the others subtypes to process the signals. Butterworth band-pass filters are designed to be maximally flat magnitude response filters, the distortion was experienced through both the passband and stopband in that range of frequency [6].

The smooth filter is a filter that is applied in the fNIRS BCI application which has a similar principle with low-pass filter, where it is used to remove the high-pass frequency noices among the signals. Even through this filter has similar principle however, this filter has numerous methods to remove the noises. There are many types of smooth filters, however the most popular that used are the moving as the moving average [21], Gaussian smoothing (Kim et al., 2019), and SavitzkyGolay smoothing filters (Shin et al., 2014). In the smooth filter, the signals can be smoothed at either the time domain where the noise is remove in the data or spatial domain that reduce the noise from poor channels that surround the fNIRS channels by averaging the signals (Wriessnegger et al., 2018)

The moving averaging smooth filter reduce the high-frequency noise by averaging together numbers of data points. The other types Gaussian applied Gaussian-weighting function, which the value at each point are multiple depending on the data distribution. One point at the center of the Gaussian along with the neighboring points is set to be weighted. However this types of filter is not suitable for fNIRS BCI application, because the filter makes the hemodynamic response distorted and unclear in the experiment [21]. The filter is also still lack of information on why the filter is appropriate for reducing high-frequency noises (Rahman et al., 2019).

B. *Feature Extraction and selection in BCI*

Feature extraction played a crucial role in the identification of the discriminatory information carried by the biosignals [12], [13]. The selection of feature extraction tools is very crucial in clinical applications the impropriate feature extraction selection may cause a significant drop in the accuracy result of the signals.

i. Statistical Extraction

To extract the signals data on BCI application, statistical is one of widely used feature extraction among researchers. To collect their data, statistical collected through the concentration changes of HbO or HbR, or both signals [6]. As statistical extraction achieved 92% and 94% of percentage in accuracy by using two and three features, these approaching extraction approved to be effective [15]. To process the extraction, there are some types of statistical feature that widely used which are Signal Mean (SM) [6], [13], [16], Signal Peak (SP) [13], [16],[17], Signal Slope (SS) [6],[13],[16],[17], Signal Skewness (S_{X_i}), and Kurtosis (K_{X_i}) [6], [7], [16], Variance ($\sigma^2_{X_i}$) [16].

$$SM = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (1)$$

$$SP = \sum_{i=1}^{N} f(|X_i - X_{i+1}|) \quad (2)$$

$$\sigma^2_{X_i} = \frac{\sum_{j=1}^{N}(X_{i,j}-\mu_{X_i})^2}{N} \quad (3)$$

$$K_{X_i} = \frac{\sum_{j=1}^{N}(X_{i,j}-\mu_{X_i})^4/N}{\sigma^4_{X_i}} \quad (4)$$

$$S_{X_i} = \frac{\sum_{j=1}^{N}(X_{i,j}-\mu_{X_i})^3/N}{\sigma^3_{X_i}} \quad (5)$$

In this equation, N represents the total of data points, meanwhile, X_i represents the signal amplitude value. In another hand, the slope is collected by computed linear regression. Although statistical has been effectively approved, the accuracy of these features decreased significantly to 67% when it was applied to four class-oriented features [18], [19].

ii. Common Spatial Pattern

Common Spatial Pattern (CSP) is feature extraction that is mostly used in BCI applications [7],[20]. CSP was designed to analyze the two-class problem in the multichannel data. The signals from multichannel are projected into subspace with a projection matrix in which each row contains of weights for channels. CSP calculates the signals by normalizing spatial covariance C from the input data E which showed in the equation below,

$$C = \frac{CC'}{tr(EE')} \qquad (6)$$

From the equation above, E is represented as an N x T matrix, where the T channels numbers (i.e. recording electrode). And N is the number of samples per channel. The apostrophe $'$ showed as the transpose operator, then $tr(x)$ is the sum of the diagonal elements of x.

When CSP feature extraction is applied to synchronous BCI applications at certain periods, it is resulting in high accuracy. However, it is the opposite of the asynchronous BCI applications where it is not giving any improvement (Nicolas-Alonso et al., 2012). Nevertheless, over-fitting affected the CSP by excessively following the dataset to estimate them (Buccino et al., 2016). In addition, this tool also gives poor generalizations on new observations (Buccino et al., 2016).

iii. Wavelet Transform

Wavelet Transform (WT) is a widely used tool among researchers to extract information from numbers of data that are audio, image data, and more (Nicolas-Alonso et al., 2012, Khan et al., 2021). Wavelets are functions of different frequencies and finite and finite duration, that allow the signals to study both time and frequency domains which differ it from other modalities such as Fourier Transform (FT) (Nicolas-Alonso et al., 2012, 31 Khan et al., 2021). Meanwhile, Fourier Transform (FT) only determines the analysis of the signal activity in the frequency domain. Wavelet Transform is used to overcome the limitation that FT had by decomposing both signal time and frequency domains at multiple scales.

WT is a powerful technique for the decomposition of transient brain signals into their constituent parts based on a combination of frequency and temporal position. The identification of signal frequency range is distinguished from means of the temporal position. It was possible for WT to separate the temporal overlap processes due to different frequency content. The concept of this WT technique is scaling and shifting. There are two significant transforms in wavelet which are, Continous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT).

The CWT was introduced with a lot of complexity and redundancy due to the incorporation of signal analysis with the highest number of frequencies using multiple dilations and mother wavelet. To overcome the limitation of CWT, DWT was introduced, this technique translates and dilates the mother wavelet in only certain discrete values. To process the data by using WT, the tool is required to select the mother wavelet. There are many different types of mother wavelets that can be used in BCI applications. However, the selection of the mother wavelet was based on types of the feature that need to be extracted from the signal. However, this approach technique contains shift sensitivity, poor direction, and lack of information (Khan et al., 2021).

iv. Principle Component Analysis

Principle Component Analysis (PCA) is mostly used to detect images through pre-processing of multispectral remote- sensing images. Meanwhile, PCA in feature extraction is also popular in dimensional reduction and statistical extraction (Khan et al., 2021, Nicolas-Alonso et al., 2012). To get the highest possible variance, this approaching technique in statistical used linear transformation to generate the principle components to be sorted. The brain signals then is being separated into different components by the variance (Khan et al., 2021, Nicolas-Alonso et al., 2012).

Dimensional reduction is another procedure done by PCA, where it produced lower dimensional output than the input. This happened because the number of columns is less than the number of eigenvectors. The tool is applied by the BCI application because of its ability that being able decreasing dimensionally in order to reduce the complexity of subsequent classifying steps (Nicolas-Alonso et al., 2012). The PCA reduces the dimension of the data by seeking the optimal representation of the data in terms of minimal mean-square error between the representation and the original data. PCA in the application of BCI has successfully identified the EEG signal's artificial components and then reconstruct the signals without the components of artificial.

v. Linear Discriminant Analysis

Another dimensional reduction extraction is Linear Discriminant Analysis (LDA). LDA dimensionally reduces the data into a smaller subspace with good class separability while maintaining the original (Lotte et al., 2007). In the BCI application, LDA is popular because of its rapid response (Nicolas-Alonso et al., 2012), simplicity, and effectiveness (Khan et al., 2021). This tool is successful in several BCI applications and also provided acceptable accuracy (Nicolas-Alonso et al., 2012) which is synchronous, classification of EEG and fNIRS for gait disorder (Naseer et al., 2016, Khan et al, 2018, Elvira et al.,2019), and many more BCIs.

LDA performs by classifying patterns into two classes where it assumes that the two classes are separate linearly. The tool then differentiates the classes through a hyperplane that is assigned by a linear discrimination function. The class that belongs to the feature vector then depends on the side of the plane where the vector is found. Mathematically the decision plane can be represented as the 2.15 equation below,

$$g(x) = W^T x + W_o \quad (7)$$

From the mathematic equation above, W is represented as the weight vector, x is the input feature vector, W_o shown as the threshold. In another hand, the assignment of the input vector to one class or the other is based on $g(x)$. Although this tool is widely used in the BCI application, nevertheless this tool has limited computational resources as its limitation (Nicolas-Alonso et al., 2012).

C. Classification in BCI application

Classification in the BCI application has an objective where it is used to recognize the user's intention based on the feature vector of the brain characterization activity that is set by the feature map (Alonso et al., 2012).

i. Convolutional Neural Network

Machine learning has been used by researchers to classify data or signals. One of the subfields used by researchers is deep learning (Gabrieli et al., 2021). Convolutional Neural Network (CNN) is one of the deep learning types that have recently popular for their automatic feature extraction and classification. CNN has been applied to several signals data from EEG, EMG, and fNIRS signals (Trakoolwilaiwan et al., 2017, Tang et al., 2017, Ho et al., 2019). This tool becomes a dominant technique because of the application that popularly used in real life than machine learning types (Krizhevsky et al., 2012, Sutskever et al., 2014) (LeCun et al., 2015

CNN is a machine-learning approach that is able to reach human-level performance in image classification (Zhang et al., 2018), and natural language processing tasks (Sutskever et al., 2014, Bahdanau et al., 2015). Another application of CNN recently is classifying motor execution and motor imaginary in fNIRS signals (A et al., 2020). The successful application of CNN in several studies makes the researchers start to use this tool for other applications such as time series analysis.

CNN consists of three layers in order to process data which are the convolutional layer, pooling layer, fully connected layer, and output layer (A et al., 2020). The layers of CNN contain layers of neuron that arranged of three dimension which are height, width, and depth.

In the convolutional layer two-dimesional convolution is performed with local regions in the two-dimesional input image of signals representation. This resulting in activation map or also called as a feature map. On another hand, downsampling is applied in the pooling layer in order to reduce the size of the pooling data and number of parameter in the network. After that, at the output a fully connected layer is connected to all the previous layer. SoftMax activation function is used in the last of fully connected layer. The used of the SoftMax is to compute the probability of each score then calculated it to find the possibility of the targer classes (Chiarelli et al., 2018). Despite all the abilities of CNN, nevertheless this tool found to rare to used in the application of fNIRS BCI application (A et al., 2020).

ii. Artificial Neural Network

Another popular machine learning approach that researchers used in many application such as computer science, physics, and neuroscience named as Artificial Neural Network (ANN) (Nicolas-Alonso et al., 2012). ANN predict the outcomr by analyzing complex interactions between a group of measurable covariates.The architecture of ANN is inspired by the behaviors of neurons signal in neural networks that contains of a population of neurons connected to each other through complex signal pathways. Mimicking the human brain as their purpose of this tool in order to solve certain problem faster than convolutional computer does.

ANN works by recognize the pattern by learning from training the data (Nicolas-Alonso et al., 2012, Rasheed., 2021). ANN has consisted of nodes and connections that are modified in the training process. The final result of this tool is being observed by the training data that has been fed into ANN. Nevertheless, the internal weights may change as the result is incorrect to minimize the the difference between desired and actual output training algorithm. The training loop keep continuing until it reaches a steady state, where there were no significant improvements. Then the trained ANN is able to recognize data related to training data patterns. ANN consists of three layers, the first one is an input layer, followed by the second one the hidden layers, and the last one is an output layer. In ANN there are activations that are used as communication among the neurons, where the weighted sum of a neuron's input is converted into an output.

ANN has been used in numbers of BCI applications, such as , multilayer perception (MLP) which is known as one of the ANN structures used in Probabilistic Neural Networks (PNN) by 253 and 254. The other application is applied in EEG signals which resulting in better classification ouput than other tools(Rasheed, 2021). ANN has ability to accommodate variable interactions and nonlinear associations. However, this technique is complex, lacks transparency, and requires large data sets as their limitations.

iii. Support Vector Machines

Support Vector Machines (SVM) is a supervised learning algorithm that widely used in many application. One of the application is in the medial field where it is used for application in prognosis and diagnosis of disease (Dallora, et al, 2017). SVM is widely used in classification and regression problem (Nicolas-Alonso et al., 2012). SVM is also a machine learning branch that popular in BCI applications as classification. This tool is performed excellently in the synchronous BCIs system with large numbers of data. The popularity of SVM in BCI applications happened because of its ability as good perform as a simple classifier, and to maintain good results this tool is not required large data (Nicolas-Alonso et al., 2012). SVM also has low misclassification error and scales well to high-dimensional data (Bi et al., 2019), and has reasonable interpretability (Bi et al., 2019)

To process their data, SVM used hyperplanes to maximize the margins, which is the distance between the nearest training samples and hyperplanes (Nicolas-Alonso et al., 2012). This tool constructs optimal boundaries in the hyperplane in order to separate the different classes of observations. SVM also named as a linear classification because of its use on one or several hyperplanes (Nicolas-Alonso et al., 2012). Nevertheless, a non-linear decision can be created by SVM by applying a kernel function which also can increase the classification accuracy. The kernel function works by separating the input to project the data into a higher-dimensional space. Even though the technique is popular in BCI applications however, SVM is a process that time-consuming and the standard of kernel functions does not guarantee the optimal function.

CONCLUSION

This paper presents a review of the process of the signals in the BCI applications that mostly used by researchers such as pre-processing, feature extraction, and classification method. There are several tools to record the signals of the brain, however EEG and fNIRS are the most popular tools among others. The recorded signal is going through a pre-processing process in order to removing the unwanted signals. Filtering is a pre-processing process that popular in BCI applications due to being quick and easy to implement. There are filtering process that widely used by researchers such as low-pass and high pass filter, band pass filter, and smooth filter. Feature extraction is another process after pre-processing where in this paper there are several techniques that mostly used which are statistical feature extraction, Common Spatial Pattern (CSP), Wavelet Transform (WT), Principle Component Analysis (PCA), and Linear Discriminant Analysis (LDA). The last is classification. where it is used as recognize the user's intention, and characterized the brain activity that set by the feature map. ANN,CNN,SVM are the types of machine learning branch that are popularly used in BCI application for classification purposes.

REFERENCES

[1] Hamid, H., Naseer, N., Nazeer, H., Khan, M. J., Khan, R. A., & Shahbaz Khan, U. (2022). Analyzing classification performance of fNIRS-BCI for gait rehabilitation using Deep Neural Networks. Sensors, 22(5), 1932

[2] Alzahab, N. A., Apollonio, L., Di Iorio, A., Alshalak, M., Iarlori, S., Ferracuti, F., Monteriù, A., & Porcaro, C. (2021). Hybrid deep learning (hdl)-based brain-computer interface (BCI) systems: A systematic review. Brain Sciences, 11(1), 75.

[3] Ma, T., Chen, W., Li, X., Xia, Y., Zhu, X., & He, S. (2021). FNIRS signal classification based on deep learning in rock-paper-scissors imagery task. Applied Sciences, 11(11), 4922.

[4] Rasheed, S. (2021). A review of the role of machine learning techniques towards brain–computer interface applications. Machine Learning and Knowledge Extraction, 3(4), 835–862.

[5] Shih, J. J., Krusienski, D. J., & Wolpaw, J. R. (2012). Brain-computer interfaces in medicine. *Mayo Clinic Proceedings*, *87*(3), 268–279.

[6] Naseer, N., & Hong, K.-S. (2015). FNIRS-based brain-computer interfaces: A Review. Frontiers in Human Neuroscience, 9.

[7] Khan, H., Naseer, N., Yazidi, A., Eide, P. K., Hassan, H. W., & Mirtaheri, P. (2021). Analysis of human gait using hybrid EEG-fNIRS-based BCI system: A Review. Frontiers in Human Neuroscience, 14.

[8] Chen, W.-L., Wagner, J., Heugel, N., Sugar, J., Lee, Y.-W., Conant, L., Malloy, M., Heffernan, J., Quirk, B., Zinos, A., Beardsley, S. A., Prost, R., & Whelan, H. T. (2020). Functional near-infrared spectroscopy and its clinical application in the field of neuroscience: Advances and future directions. Frontiers in Neuroscience, 14.

[9] Herold, F., Wiegel, P., Scholkmann, F., & Müller, N. (2018). Applications of functional near-infrared spectroscopy (FNIRS) neuroimaging in Exercise–Cognition Science: A Systematic, methodology-focused review. Journal of Clinical Medicine, 7(12), 466.

[10] Liu, J., Song, T., Shu, Z., Han, J., & Yu, N. (2021). FNIRS feature extraction and classification in grip-force tasks. *2021 IEEE International Conference on Robotics and Biomimetics (ROBIO)*.

[11] Baker, W. B., Parthasarathy, A. B., Busch, D. R., Mesquita, R. C., Greenberg, J. H., & Yodh, A. G. (2014). Modified beer-lambert law for blood flow. Biomedical Optics Express, 5(11), 4053.

[12] Ortega, P., Zhao, T., & Faisal, A. A. (2020). HYGRIP: Full-stack characterization of neurobehavioral signals (fNIRS, EEG, EMG, force, and breathing) during a bimanual grip force control task. Frontiers in Neuroscience, 14.

[13] Sattar, N. Y., Kausar, Z., Usama, S. A., Farooq, U., Shah, M. F., Muhammad, S., Khan, R., & Badran, M. (2022). FNIRS-based upper limb motion intention recognition using an artificial neural network for transhumeral amputees. Sensors, 22(3), 726.

[14] Ortega, P., Zhao, T., & Faisal, A. A. (2020). HYGRIP: full-stack characterization of neurobehavioral signals (fNIRS, EEG, EMG, Force, and Breathing) during a bimanual grip force control task. Frontiers in Neuroscience, 14, 919.

[15] Naseer, N., Noori, F. M., Qureshi, N. K., & Hong, K.-S. (2016). Determining optimal featurecombination for LDA Classification of functional near-infrared spectroscopy signals in braincomputer interface application. Frontiers in Human Neuroscience, 10.

[16] Erdoĝan, S. B., Özsarfati, E., Dilek, B., Kadak, K. S., Hanoĝlu, L., & Akın, A. (2019). Classification of motor imagery and execution signals with population-level feature sets: Implications for probe design in fNIRS based BCI. Journal of Neural Engineering, 16(2), 026029.

[17] A, J., M, S., Chhabra, H., Shajil, N., & Venkatasubramanian, G. (2020). Investigation of deep convolutional neural network for classification of motor imagery fNIRS signals for BCI applications. Biomedical Signal Processing and Control, 62, 102133.

[18] Robinson, N., Zaidi, A. D., Rana, M., Prasad, V. A., Guan, C., Birbaumer, N., & Sitaram, R. (2016). Real-time subject-independent pattern classification of overt and covert movements from fnirs signals. PLOS ONE, 11(7).

[19] Ong, J. H., & Chia, K. S. (2021). Principal components-artificial neural network in functional nearinfrared spectroscopy (FNIRS) for Brain Control Interface. 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT).

[20] Nicolas-Alonso, L. F., & Gomez-Gil, J. (2012). Brain Computer Interfaces, a review. Sensors, 12(2), 1211–1279.

[21] Groff, B. R., Antonellis, P., Schmid, K. K., Knarr, B. A., & Stergiou, N. (2019). Stride-time variability is related to sensorimotor cortical activation during forward and backward walking. Neuroscience Letters, 692, 150–158.

[22] Kim, H. Y., Kim, E. J., & You, J. (S. (2017). Adaptive locomotor network activation during randomized walking speeds using functional near-infrared spectroscopy. Technology and Health Care, 25, 93–98.

[23] Shin, J., & Jeong, J. (2014). Multiclass classification of hemodynamic responses for performance improvement of functional near-infrared spectroscopy-based brain–computer interface. Journal of Biomedical Optics, 19(6), 067009.

[24] Wriessnegger, S. C., Bauernfeind, G., Kurz, E.-M., Raggam, P., & Müller-Putz, G. R. (2018). Imagine squeezing a cactus: Cortical activation during affective motor imagery measured by functional near-infrared spectroscopy. Brain and Cognition, 126, 13–22.

[25] Rahman, M. A., Rashid, M. A., & Ahmad, M. (2019). Selecting the optimal conditions of Savitzky– Golay filter for fNIRS signal. Biocybernetics and Biomedical Engineering, 39(3), 624–637.

[26] Buccino, A. P., Keles, H. O., & Omurtag, A. (2016). Hybrid EEG-fnirs asynchronous brain-computer interface for multiple motor tasks. PLOS ONE, 11(1).

[27] Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., & Yger, F. (2018). A review of classification algorithms for EEG-based brain–computer interfaces: A 10 Year update. Journal of Neural Engineering, 15(3), 031005.

[28] Elvira, M., Iáñez, E., Quiles, V., Ortiz, M., & Azorín, J. M. (2019). Pseudo-online BMI based on EEG to detect the appearance of sudden obstacles during walking. Sensors, 19(24), 5444.

[29] Elvira, M., Iáñez, E., Quiles, V., Ortiz, M., & Azorín, J. M. (2019). Pseudo-online BMI based on EEG to detect the appearance of sudden obstacles during walking. Sensors, 19(24), 5444.

[30] Gabrieli, G., Bizzego, A., Neoh, M. J., & Esposito, G. (2021). FNIRS-QC: Crowd-sourced creation of a dataset and machine learning model for fNIRS Quality Control. Applied Sciences, 11(20), 9531.

[31]

[32] Tang, Z., Li, C., & Sun, S. (2017). Single-trial EEG classification of motor imagery using deep convolutional neural networks. Optik, 130, 11–18.

[33] Ho, T. K., Gwak, J., Park, C. M., & Song, J.-I. (2019). Discrimination of mental workload levels from multi-channel fNIRS using deep leaning-based approaches. IEEE Access, 7, 24392–24403.

[34] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional Neural Networks. Communications of the ACM, 60(6), 84–90.

[35] Sutskever I, Vinyals O, Le QV (2014) Sequence to sequence learning with neural networks. In: Neural information processing systems, pp 3104–3112

[36] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.

[37] Zhang, H., Chen, B., Wang, Z., & Liu, H. (2019). Deep Max-margin discriminant projection. IEEE Transactions on Cybernetics, 49(7), 2454–2466.

[38] Bahdanau D, Cho K, Bengio Y (2015) Neural machine translation by jointly learning to align and translate. In: International conference on learning representations

[39] Chiarelli, A. M., Croce, P., Merla, A., & Zappasodi, F. (2018). Deep learning for hybrid EEG-FNIRS BRAIN–computer interface: Application to motor imagery classification. Journal of Neural Engineering, 15(3), 036028.