Engineering Journal issn: 0125-8281

Review

Developing an Optimal Brain Computer Interface Model using Functional Near Infrared Spectroscopy: A Review

Jia Heng Ong[1,2,a] **and Kim Seng Chia**[1,b,*]

1 Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Johor, Malaysia
2 Merry Electronics (Singapore) Pte. Ltd., Singapore
E-mail: [a]ongjiaheng0612@gmail.com, [b,*]kschia@uthm.edu.my (Corresponding author)

Abstract. Brain-Computer Interfaces (BCIs) are promising in advancing numerous applications. Although many functional near-infrared spectroscopy (fNIRS)-based BCIs have been studied, the development of an optimal fNIRS-based BCI model remains unclear. This study aims to review recent methodologies that used to optimize fNIRS-BCI models in four aspects i.e. signal acquisition, pre-processing, feature extraction, and machine learning. Besides, the differences, strengths, and limitations of various algorithms are discussed and highlighted. By comprehensively examining the recent trends and challenges in fNIRS BCI model development, this study proposes and discusses potential techniques in advancing fNIRS-based BCIs model development. The results suggest that future fNIRS-based BCI studies should focus on addressing cross-subject classification challenges and real-world fNIRS-BCI applications.

Keywords: Functional near infrared spectroscopy, brain computer interface, machine learning, review.

ENGINEERING JOURNAL Volume 27 Issue 10
Received 22 March 2023
Accepted 28 September 2023
Published 31 October 2023
Online at https://engj.org/
DOI:10.4186/ej.2023.27.10.21

DOI:10.4186/ej.2023.27.10.21

1. Introduction

Brain imaging technologies fall into two categories: invasive and non-invasive. Invasive approaches, such as Electrocorticography (ECoG), Stereo-encephalography (SEEG), and Endovascular Electrocorticography, require sensor arrays to be implanted via surgery, which can provide high-quality brain activity data [1]. Non-invasive approaches, such as Functional Magnetic Resonance Imaging (fMRI), Electroencephalogram (EEG) and functional near-infrared spectroscopy (fNIRS), are commonly used in BCI applications due to their simplicity in measurement setup and flexibility in conducting research study. Although non-invasive methods have relatively weaker performance due to uncontrollable scalp conditions and signal decay, these methods are more widely accepted as they are relatively safer than invasive methods. With the aid of machine learning models, EEG and fNIRS are used in psychiatric treatment and analysis for conditions like Obsessive-Compulsive Disorder (OCD) [2], Locked-in Syndrome (LIS) [3], and Parkinson's Disease (PD) [4], as well as in non-medical purposes like prosthetic legs controls [5], and drone remote control [6].

Recent review studies have indicated that current Brain Control Interface (BCI) modalities are still in the pre-clinical and clinical stages [1]. To enhance the potential of these modalities for domestic use, recent review suggests that future studies should focus on ultraportable BCI modalities [7] and develop an efficient feature fusion framework for hybrid fNIRS-EEG BCI [8], which might improve their latency and spatial resolution [9], [10]. Even though machine learning plays a crucial part in establishing a relationship between the acquired fNIRS signals and the components of interest, there is a lack of comprehensive review for researchers to stay on track with the recent fNIRS-BCI machine learning modelling development. Therefore, this study aims to provide a holistic review of recent fNIRS-BCI studies and presents them in terms of development stages as that illustrated in Fig. 1, i.e., fNIRS signal acquisition (Section 3), signal pre-processing (Section 4), feature extraction (Section 5), and BCI machine learning (Section 6). Finally, we present our discussion and conclusion that related to the fNIRS-BCI real-life implementation in Section 7.

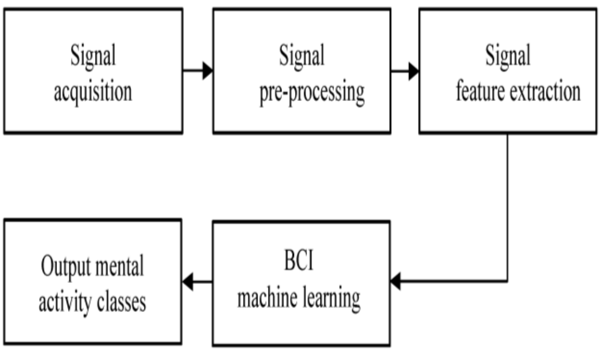

Fig. 1. The five phases in developing a machine learning for BCI using fNIRS.

2. Scope of Review

This study used the Scopus database to search the relevant Scopus-indexed journal articles from 2016 to 2021 using the keywords "fNIRS" or "Functional Near Infrared Spectroscopy" and "BCI" or "Brain Control Interface". After screening based on title and abstract relevance, and excluding irrelevant articles, a total of 71 articles were reviewed in this study. Figure 2 presents the proportion of mental tasks and algorithms for each process based on the shortlisted studies. Additional seven references were included to support the explanations.

3. FNIRS Data Acquisition

A fNIRS probe is normally made of near infrared (NIR) light emitting diode (LED) and optode arrays with fixed or adjustable source-optodes spacing distance. Most commercial fNIRS systems employ a continuous NIR light source within the wavelength range of 650-850nm to avoid signal contamination that caused by water absorption beyond 900nm [11]. In data acquisition process, a probe is mounted on the scalp of a subject on the region of interest. Aside from the commercialised probes, researchers have developed portable prototypes to improve the competitiveness of fNIRS modalities, including a palm-sized fNIRS spectroscopy device that used an Arduino microcontroller and wavelet transform analysis for brain activity analysis [12]. Other studies aimed to create economical and sensitive portable fNIRS prototypes for topology study [13].

During brain activity signals collection process with fNIRS, NIR photon would penetrate the brain and then follow a "banana-shaped" trajectory, reflecting, scattering, and being absorbed by water, haemoglobin, cytochromes, and other compositions of human blood as it flows through the cortex. The changes of blood flow in a specific cortex can be predicted by measuring the loss of NIR light intensity using optodes [14]. In fNIRS-BCI processing, the modified Beer-Lambert Law (MBLL) method is used to convert light intensity into changes in blood oxy- and deoxygenated haemoglobin concentrations ($\Delta C^i_{Hbo}(t)$ and $\Delta C^i_{HbR}(t)$). Conventional fNIRS probes typically operate with two light source wavelengths, and the molar extinction coefficient for the specific wavelength is used to compute concentration changes, ΔC using Eq. (1) [15].

$$\begin{pmatrix} \Delta C^i_{HbO}(t) \\ \Delta C^i_{HbR}(t) \end{pmatrix} = \begin{pmatrix} \varepsilon_{HbO}(\lambda_1)\varepsilon_{HbR}(\lambda_1) \\ \varepsilon_{HbO}(\lambda_2)\varepsilon_{HbR}(\lambda_2) \end{pmatrix}^{-1} \cdot \begin{pmatrix} \Delta OD^i(t,\lambda_1) / \dfrac{\partial \mu}{\partial A} \\ \Delta OD^i(t,\lambda_2) / \dfrac{\partial \mu}{\partial A} \end{pmatrix} \quad (1)$$

3.1. Types of FNIRS-BCI Experiment

The experimental design of a type fNIRS-BCI study involves subject sample population and mental task

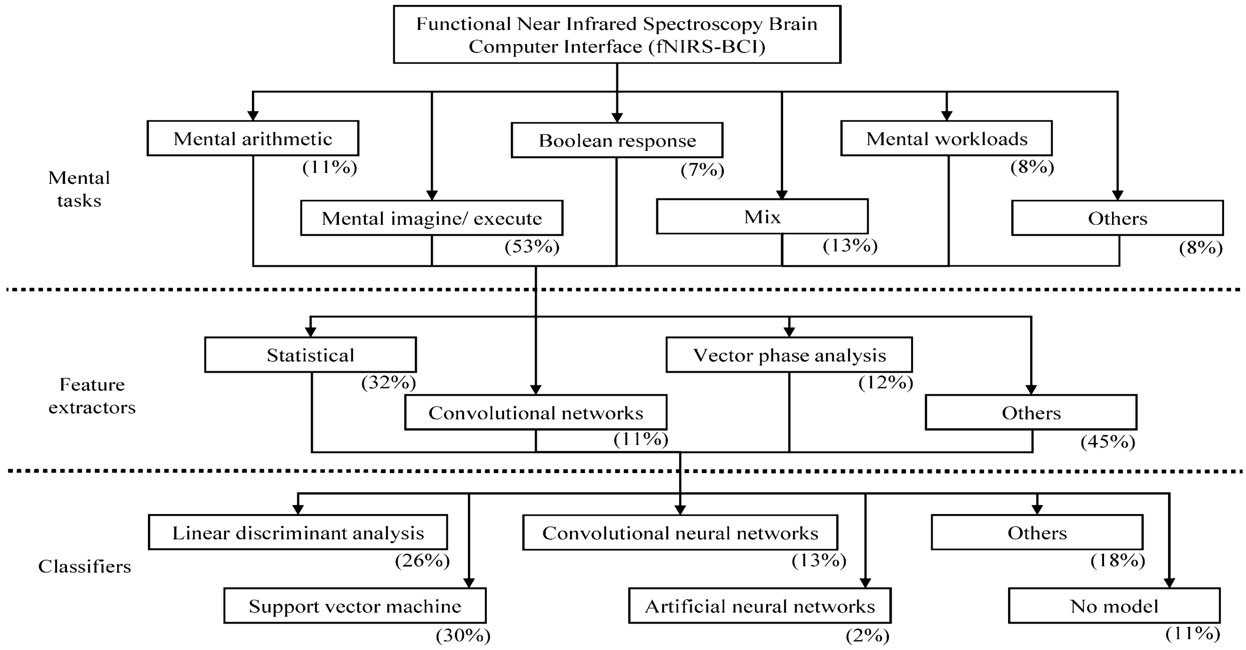

Fig. 2. The composition of mental tasks, feature extractors, and classifiers in fNIRS-BCI studies that reviewed in this study (published from 2016 to 2021).

variants. Most studies prefer subjects between 20 to 40 years old, with good health and no drug intake or no brain disorder history for sample homogeneity concern. While some studies implemented fNIRS-BCI on actual patients, they showed that signals from patients, especially with limited training sample size, were challenging for BCI applications [16]–[18]. Signal sample augmentation through Generative Adversarial Networks (GANs) may help for solving the sample size limitation problem that caused by subjects' health conditions [19], [20]. This augmentation approach can potentially improve the accuracy of classification models on datasets with intra-classes imbalances, eliminating the need for additional sample preprocessing algorithms such as k-means clustering [21].

Based on Fig. 2, mental tasks examined in fNIRS-BCI consisted of mental arithmetic (11%), mental imagery or execution (53%), boolean responses (7%), mental workload (8%), mixed tasks (13%), and others (8%). Mental arithmetic experiments usually required participants to perform calculations or read text, while mental imagine or execution tasks involved imagining or executing body actions. Boolean response tasks required participants to react to logical problems with "Yes" or "No" responses [22]. Mental workload experiments focused on mental stresses during specific activities, such as flight pilot training [23] or driving [24]. Other experiments including eye tracking and virtual graphic reaction to collect trainable brain activation feedback for computer interfaces [25]. Visual task-based brain activities were commonly used for graphical user interface control [26]. Each instruction execution had a pre-defined rest-task timing ratio to prevent mind interruption, with intermediate rest included for mental reset.

Mixed tasks consisted of multiple independent brain activities in different task sessions, which posted higher class classification complexity. Concerning the mental class variants specification, mental imagine task is expected to excite least brain motor area compared to other tasks e.g. body execution and observation through eye. Performing total cerebral lobes dependency analysis for a mental task is tedious and less interpretable without the aid of high precision lobes scanning using fMRI and mathematical modelling [27]. Alternatively, a preliminary amplitude-based analysis can be performed to pinpoint the activation region for the specific mental tasks. Figure 3 illustrates the interpolated neuron activation area from 15 subjects when performing the mentioned mental tasks [28]. Hence, it is crucial to take the mental task nature into consideration when designing experiments for fNIRS data acquisition for the concern of tasks significance.

Overall, the current fNIRS-BCI models mainly focus on the classification of mental class variants for BCI applications in more complex tasks, such as wrist angle

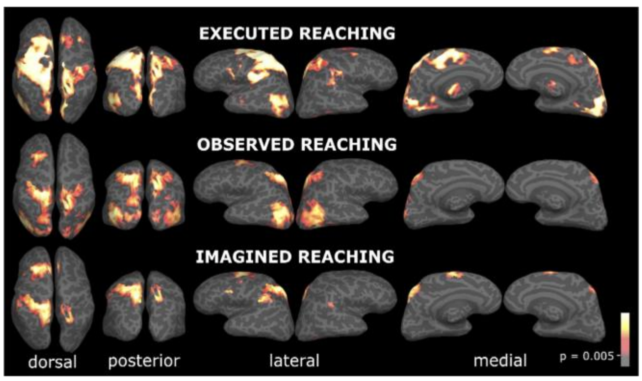

Fig. 3. The illustration of group surface-averaged activations collected using fMRI when mental executed, observed, and imagined tasks, versus baseline were performed [28].

DOI:10.4186/ej.2023.27.10.21

manipulation [29], different speech contents [30], and puzzle path planning imagination [31]. While these preliminary studies show promising results, they are still in their early stages and require further validation in future clinical trials.

4. Signal Pre-processing

The non-invasive nature of fNIRS makes its brain activity signal quality highly susceptible due to unstable blood flow conditions, high hair density, and poor sensor contact. These factors can lead to global physiological noise that contaminates the recorded primary signal channel. To address this issue, digital noise separation techniques can be implemented, such as frequency-based Butterworth bandpass filter, short channel separation, wavelet transforms, and other filters such as Kalman filter and Savitzky-Golay. Kalman filter has shown promising performance enhancement in pilot workload classification [32]. However, the dynamic model of the fNIRS signal can be complicated, and making it challenging to ensure a high correlation between raw and processed signals. On the other hand, Savitzky-Golay signal pre-processing performance is sensitive to the filter's order and frame. Consequently, it requires continuous optimal solution search in most cases [33].

4.1. Frequency- based Filters

In fNIRS-BCI signal pre-processing, physiological responses such as human respiration, Mayer wave, and facial motion artefacts are commonly present within a specific frequency range. Frequency-based filters such as Butterworth and finite impulse response (FIR) filters are used to separate these periodic physiological signals. The range of frequency for separating these signals is typically 0.2-0.6Hz for respiratory, 0.1Hz for Mayer wave, and 0.6-2.5Hz for cardiac interference. The noise region is typically 0.01-0.15Hz for blood pressure variation, vasoreactivity, and carbon dioxide concentration [34]. Butterworth filters are commonly used due to their lower computational costs and smaller order requirements (i.e., less than six order) compared to FIR filters [35].

4.2. Short Channel Separation

In fNIRS, short channels that consist of a pair of source and optodes with a normal distance of 0.5 to 10mm are used to record brain responses from the superficial layer. It is worth to highlight that the signals might capture body artefacts and environmental noise components. Figure 4 presents the concept of short channel implementation in fNIRS probe. Short channels can be used for noise suppression in the main channel components through two approaches: direct deduction and clean signal regression using a general linear model (GLM). The direct deduction approach subtracts the short channel response from the signal response [36], while the GLM approach utilizes a Gaussian spatial filter and a short separation GLM-based haemodynamic response predictor to separate the short-channel processed signals [37]. The GLM approach can be further improved by incorporating temporal canonical correlation analysis (tCCA) in input response processing [38].

4.3. Wavelet Transform Filter

fNIRS and EEG time-series signals are often pre-processed using wavelet transform filter. This method decomposes the recorded brain activity responses into the time-frequency space and identifies contaminant frequency points based on an appropriate criterion. The contaminated coefficients are then set to zero, and the processed signal is transformed back into time-series form [39]. To further reduce the global trend of psychological noise in the signal, a wavelet transform-based signal filter is typically applied in conjunction with frequency bandpass filters. This approach often results in a more coherent signal [40]. The discrete wavelet transform algorithm has been shown to outperform other methods,

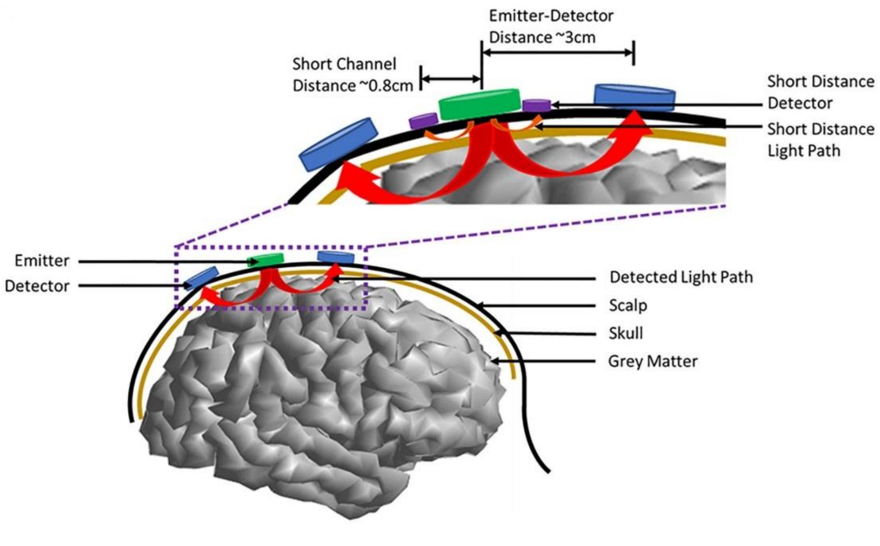

Fig. 4. The conceptual illustration of short channel signal acquisition unit on fNIRS probe [78].

such as frequency bandpass, correlation-based signal improvement, median, Savitzky-Golay, and independent component analysis (ICA), based on contrast-to-noise ratio (CNR) metrics [41].

5. Signal Feature Extraction

The selection of optimal representational features is critical for excellent classification model training, especially for single-trial BCI applications. Figure 2 shows that feature extraction algorithms can be broadly categorized into three main approaches: statistical (32%), vector phase analysis (12%), and convolutional networks (11%). Other approaches (45%) include regression-based feature extractors and novel approaches, such as the Boynton canonical hemodynamic response function (HRF) [37], estimated coefficients from the signal general linear model (GLM) [42], sharp-wave ripple (SWR) algorithm, and Relief algorithm [43]. More studies are needed to study these feature extractors in different applications. The three main feature extractors are further reviewed in the following subsections.

5.1. Statistical Feature

Statistical feature extraction is the dominant signal encoding approach in fNIRS-BCI studies and is often used as the benchmark target for algorithm validation. This approach involves projecting the signal window into statistical parameters such as peaks, means, slope, skewness, latency, kurtosis, and spectral power density. Since statistical extraction is a mature technique, there is limited room for improvement from an algorithmic perspective. Therefore, most studies focus on improving BCI model performance by manipulating parameter combinations and using different feature selector algorithms [44]–[46]. Statistical features have been proven effective in binary class against rest classification, achieving classification accuracy of over 91% with 2-3 features in a single trial [46]. However, performance decrements have been observed in non-binary and hybrid BCI problems, with average accuracies ranging from 67% to 70.5% for all classes [22]. Statistical features may not be sufficient to represent key differences between samples when mental class variants are complex. Therefore, it is important to consider the complexity of mental classes when utilizing statistical features in fNIRS-BCI machine learning models.

5.2. Vector Phase Analysis (VPA)

Vector phase analysis (VPA) is a technique that can encode the fNIRS hemodynamic response into four other parameters, including cerebral blood volume (ΔCBV), variation of cerebral oxygen exchange (ΔCOE), flow vector magnitude, and vector angle (k). Studies have shown that using VPA features in BCI models can outperform statistical-based methodologies. Hong *et al.* demonstrated that using VPA features could improve model accuracy by at least 20% compared to statistical-based BCI models in "mental execute vs rest" binary classification [3]. In addition, combining statistical and VPA features can achieve classification accuracy higher than 90% in binary classes such as mental execute and drowsiness detection [47], [48].

Temporal VPA features, such as the initial dips feature, are also beneficial in fast fNIRS feature identification. The initial dip concept suggests that the unique brain activation pattern when starting a mental task can be used as inputs for signal sample classification. However, Jiao *et al.* found that a model trained using only the initial dips feature was weaker than the five statistical feature-based models, with accuracies of 57.5% and 65.9%, respectively [49]. To optimize the initial dips-based model, the values of both signal window block and response record duration shall be optimized [50], [51].

5.3. Convolutional Layer Feature Map

A Convolutional Neural Network (CNN) can be used as a feature extraction approach to simplify data pre-processing by means of minimizing the need of manual feature selection. In this approach, fNIRS signals are presented in a two-dimensional spectrum amplitude bitmap, which is supplied to convolutional layers for pattern feature extraction. The resultant feature maps can be applied for classification using the Softmax layer in CNN or adapted as training inputs using classical machine learning algorithms. Most convolutional feature maps fNIRS-BCI models achieved an average accuracy of 90%, regardless of the classifiers used [24]. Furthermore, CNN are effective in extracting both fNIRS and EEG features. This simplifies the complexity of a hybrid BCI using EEG and fNIRS in multiple bandwidths, which is considered as a recent trend in fNIRS studies [52]. Unlike statistical analysis for fNIRS and Common Spatial Pattern (CSP) for EEG signals that require multiple feature extractors [53], [54], CNN approach allows signals from different modalities to share the same signal processing framework. Consequently, the need of multiple feature extractors in a single BCI system is eliminated. Additionally, a CNN feature-based hybrid BCI system that achieved an outstanding average classification accuracy of 99.64% in a four-class classification [55] indicates the potential for implementation of CNN in cross-subject sample prediction to reduce the need for model recalibration [56].

6. Machine Learning

Machine learning, as a classifier, is crucial in achieving high classification performance in fNIRS-BCI. This review indicates that Support Vector Machine (SVM) (30%) was the most commonly used classifiers in previous studies, followed by Linear Discriminant Analysis (LDA) (26%), CNN (13%), and Artificial Neural Network (ANN) (2%). Other common benchmark machine learning algorithms (18%) include k-nearest neighbours (KNN) [38], Navies Bayer's [5], quadratic discriminant analysis

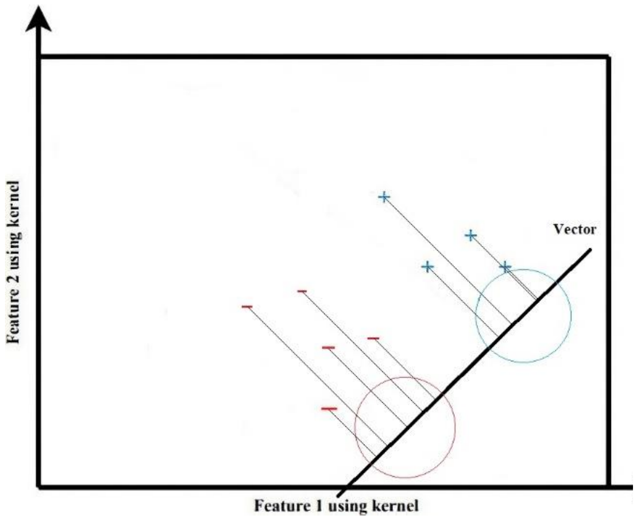

Fig. 5. The concept of hyperplane separation data grouping using LDA in classification.

(QDA) [44], etc. In 11% of the studies, the focus was on signal pre-processing algorithms benchmark or signal response analysis, and no classification model was developed in those studies [41], [57]. The four main machine learning algorithms are further reviewed in the following subsections.

6.1. Linear Discriminant Analysis (LDA)

The primary mechanism behind Linear Discriminant Analysis (LDA) is by separating the data group using a discriminant hyperplane. It continuously maximises the barrier between the potential data groups and minimises the interclass variance across process iterations, as presented in Fig. 5.

At the initialisation of the data separation stage, the inputs are defined as normally distributed and equivalent to the covariance matrix for both data groups. Subsequently, LDA would continuously update the data classes' common projection vector (*v*) and maintain the variance variations at the minimum state. The projection vector, *J* would be calculated based on Eq. (2):

$$J(v) = \frac{v^T S_b v}{v^T S_w v} \tag{2}$$

Where S_b and S_w represent the scatter matrices between and within the class, respectively. They are defined as in Eq. (3) and (4), respectively.

$$S_b = (m_1 - m_2)(m_1 - m_2)^T \tag{3}$$

$$S_w = \sum_{x_n \in C_1} (x_n - m_1)(x_n - m_2)^T + \sum_{x_n \in C_2} (x_n - m_1)(x_n - m_2)^T \tag{4}$$

Where, m_1 and m_2 are the means of the data group C_1 and C_2, respectively. At the same time, x_n is referred to as the samples. Hence, the hyperplane vector can be reformulated into a generalised eigenvector form as Eq. (5).

$$S_w^{-1} S_b v = \lambda v \tag{5}$$

The eigenvector with the largest eigenvalue, $S_w^{-1} S_b$ would be concluded as the optimal vector or can be computed directly with Eq. (6).

$$v = s_w^{-1}(m_1 - m_2) \tag{6}$$

After completing the optimal vector search, the LDA model can readily classify classes [58]. LDA is widely implemented in fNIRS-BCI model development due to the model architecture simplicity feature, majorly in binary-class classification using statistical features [59]. Recent innovations had extended the usage of LDA as a part of ensemble model [60], adaption of statistical and vector feature analysis as hybrid features [50] for performance enhancement in multi-class BCI application.

6.2. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a classifier that separates samples into groups using a hyperplane. The SVM model fitting involves iteratively adjusting the hyperplane or separation barrier based on the data. During training, the SVM searches for the optimum hyperplane gradient and increases the margin of its separation plane to the maximum, as illustrated in Fig. 6. SVM outperforms Linear Discriminant Analysis (LDA) in most cases. For instance, in a study by Khan *et al.*, where statistical features were used to classify the mental workload of prosthetic leg control in the walk-rest scenario, SVM achieved a higher averaged accuracy of 75% compared to other classifiers, i.e., k-Nearest Neighbour, quadratic discriminant analysis, linear discriminant analysis, and Naïve Bayes [5]. Besides, Almulla *et al.* applied similar benchmark classifiers with statistical features to classify mental activation responses in the sit-rest and stand-rest scenario, and the SVM model trained using slope and neutral features achieved the highest accuracy of 85% [44].

6.3. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is mainly used for image-based classification, with built-in convolutional layers serving as promising sample feature extractors in unsupervised operations. In fNIRS, CNN classifiers can be trained as optimal channel selectors [24] or brain activity classifiers [61], [62]. Unlike traditional machine learning algorithms, CNN possesses strong image processing capabilities that reduce the need for an independent signal feature extractor in classification. Some studies even suggest that signal pre-processing may degrade CNN classification performance [63]. However, building an fNIRS-BCI model using a scratch-built CNN structure is expected to increase the overall model training time by two to six times compared to classical machine learning models [64]. To address this training time issue, the adaption of pre-trained models such as EEGNET is preferred for fNIRS-BCI model development [56].

CNNs are also capable of simplifying the hybrid fNIRS-EEG BCI system framework with promising classification accuracy. Signals from different brain imaging technologies can be analyzed using CNN networks [24], [55], [65]. Alternatively, Long Short-Term Memory (LSTM) networks provide another solution by processing fNIRS signals in continuous series form. This approach is expected to enhance classifier performance by including the dynamic feature of signals when propagated in time series space, which is lacking in image-based CNNs that use discrete bitmap samples [53]. The performance enhancement using LSTM networks was justified in a side-by-side model accuracy comparison [66]. In fNIRS-BCI, Ma *et al.* reported a high averaged accuracy of 98.6% for left-right imagination mental activities classification by analyzing fNIRS signals in CNN-time series-based inputs [67].

6.4. Artificial Neural Network (ANN)

An ANN architecture typically consists of three main parts: the input layer, hidden layer, and output layer. The input layer receives the input and propagates it to the hidden layer, while the hidden layer is responsible for information processing. Compared to other linear regression classifiers, ANNs tend to achieve a higher accuracy and faster processing speed due to their parallel processing architecture and hidden neurons [68], [69]. However, a highly complex network architecture does not necessarily lead to a significant improvement in model accuracy. A recent study has shown that a single hidden layer ANN outperformed a multi-hidden layer ANN in a 4-class fNIRS-BCI problem [70]. Hence, determining the optimal number of hidden neurons is crucial for enhancing overall ANN performance.

While there are fewer studies on ANN-based BCI development compared to SVM and LDA approaches, ANN classifiers have generally outperformed the other algorithms in most cases [64]. Additionally, Erdogan *et al.* found that ANN was at least 1% better than SVM in binary classification of mental imagery and execution against the rest state using only statistical features of hemodynamic responses [71].

7. Conclusion

Near-infrared spectroscopy (NIRS) has been expanded its applications in the neurology field as a non-invasive brain imaging modality, referred to as functional near-infrared spectroscopy (fNIRS). Researchers have sought to incorporate fNIRS into brain-computer interfaces (BCIs) following the success of electroencephalogram (EEG) based BCIs. This review of 71 recent studies revealed that the fNIRS-BCI development process can be broken down into four primary stages, i.e., signal acquisition, noise separation, feature extraction, and classification.

In the signal acquisition stage, mental task experiments were performed to elicit different mental states. Real-imagine motion and visual control tasks were the most (51%) and least (1%) frequently used mental classes, respectively. This might be due to fNIRS signal responses are being more reactive during real body actions

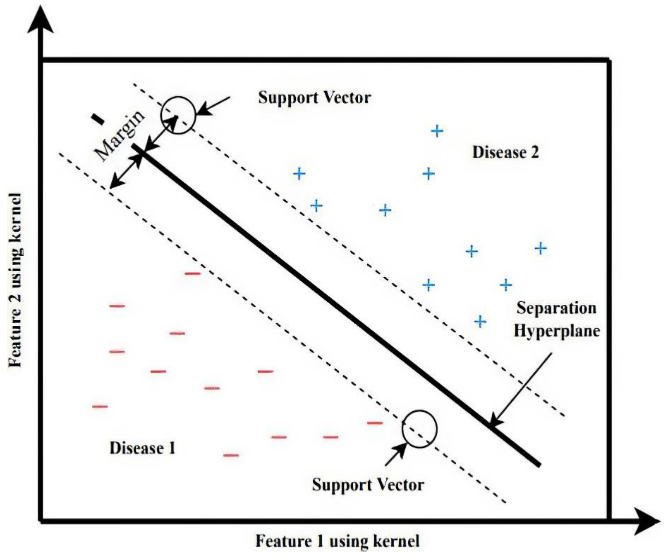

Fig. 6. The concept of hyperplane optimisation data grouping using SVM in classification.

compared to fully imagined mental tasks. Consequently, fully imagined and visually stimulated mental tasks were more challenging to analyze in fNIRS-BCI. However, fully imagined mental tasks are crucial for individuals with locked-in syndrome in daily communication applications [72]. Future studies should focus on advancing these mental classes.

In the noise separation stage, bandpass filters were commonly used in fNIRS-BCI studies for removing motion artefacts. However, it is important to note that most of the filter performance benchmark studies were conducted using self-collected datasets. Consequently, direct accuracy comparisons between studies that used different datasets are less meaningful. To enhance research transferability and reduce biases, it is recommended to use publicly accessible datasets for filter performance analysis.

The feature extraction process in fNIRS-BCI has seen innovation in recent years, with 45% of studies reported new feature extraction methods, followed by statistical (33%), vector phase analysis (12%), and convolutional layers (10%). However, these feature extractors have drawbacks, such as weak performance for non-binary BCI problems, sensitivity to fNIRS response latency, and high computation power requirements. Hybrid fNIRS-EEG-based BCI has been proposed with promising results, but it requires supports from different feature extractors [73], and model combinations [74]. As a result, the computation cost would be increased. Thus, future study may focus on improving the computation framework of hybrid fNIRS-EEG BCI, such as system simplification by channel reduction [56], universal features in CNN feature maps [75], and k-mean clustering coefficient [76].

Next, recent fNIRS-BCI studies have shown a gradual shift from classical machine learning classification to deep learning. Related suggestions have been highlighted in most studies to use these advanced techniques [77]. The adaptation of LSTM and pre-trained networks, such as EEGNET, into fNIRS-BCI model development, have reduced the requirement of signal sample size for model training or calibration [56]. Cross-validation is essential for BCI model evaluation, and the feasibility of leave-one-subject-out cross-validation [56] or subject-independent prediction [40] shall be advocated to evaluate the performance of fNIRS-BCI models to avoid over-optimistic models. Thus, future studies should focus on evaluating the optimized model using cross-subject prediction.

Lastly, this review indicates that the transfer learning-based model will be the next trend of fNIRS-BCI studies due to the integrated and self-optimised feature extractor layers. Cross-subject classification and BCI model simplification should be focused on to overcome the limitation of fNIRS-BCI when it is practically used. Besides, fNIRS shall be studied in more complicated applications in the future.

Acknowledgement

The authors would like to acknowledge to Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia for providing supports and facilities for this study. This research was supported by the Ministry of Higher Education (MOHE) through the Fundamental Research Grant Scheme (FRGS) FRGS/1/2020/ICT02/UTHM/03/6.

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Jia Heng Ong was born on June 12, 1996, in Johor, Malaysia. He was awarded with Bachelor's Degree of Mechanical Engineering with Honours from Universiti Tun Hussein Onn Malaysia, Batu Pahat, Johor, Malaysia in 2020. In 2023, he had completed his Master's Degree of Electrical Engineering by full research from the same institution with the primary focus of a study on the advancement of signal processing and machine learning technology, specifically for the functional near-infrared spectroscopy in brain computer interface application (fNIRS-BCI).

Mr. Ong is currently affiliate under Merry Electronics (Singapore) Pte. Ltd. as a software firmware engineer. He is active in the research and development of the high-end acoustic products and providing robust embeded system solution that leads to mass productions.

Kim Seng Chia was born in Batu Pahat, Johor, Malaysia in 1986. He obtained his PhD (electrical engineering) and BEng (electronic engineering – control & instrumentation) from Universiti Teknologi Malaysia in Feb. 2014 and Sept. 2010, respectively.

He has professionally registered with Engineering Council as Chartered Engineers (CEng) through The Institution of Engineering and Technology (IET) since Nov. 2020. He has also professionally registered Board of Engineers Malaysia (BEM) as Professional Engineer since Mac. 2023. Currently, he serve as an Associate Professor in the Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Batu Pahat, Malaysia.

Assoc. Prof. Ir. Dr. Chia has been the principal investigator of more than nine research grants since 2014. He is the corresponding author of more than 36 peer reviewed research articles. His research interests are machine learning, artificial intelligence, real-time embedded system, internet of things, and near infrared spectroscopic analysis.