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A systematic review on hybrid EEG/fNIRS in brain-computer interface

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ABSTRACT

As a relatively new field of neurology and computer science, brain computer interface (BCI) has many established and burgeoning applications across scientific disciplines. Many neural monitoring technologies have been developed for BCI studies. Combining multiple monitoring technologies provides a new approach that synthesizes the advantages and overcomes the limitations of each technology. This article presents a systematic review on the applications, limitations, and future directions for the hybridization of electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) into one synchronous multimodality. This review investigated research questions on design and usability of hybrid EEG-fNIRS studies. In this article, 765 papers were included in the initial search and 128 papers were selected through the PRISMA protocol. The review results show the possibility of improving the performance of hybrid EEG-fNIRS by optimizing the feature extraction algorithms and physical designing as well as expending more possible applications in information processing related fields.

1. Introduction

Brain computer interface (BCI) translates brain activity associated with a subject's intention into commands to communicate with or control an external device, bypassing the physiological motor output system. With the development of BCI, many prospective applications have been proposed for mental health and disabilities for individuals. BCI research has been considered as an effective approach to assist people with physical disabilities and mental diseases.

To maximize the application effect of BCIs, an optimized signal collector is required to obtain real-time information from brain activity in a convenient and effective method, with less set-up time and long-term stability. Currently, popular BCI monitoring technologies include Electroencephalography (EEG) [1], functional Magnetic Resonance Imaging (fMRI) [2], Magnetoencephalography (MEG) [3] and functional Near-Infrared Spectroscopy (fNIRS) [4], which each have their own advantages and limitations. Combining multiple monitoring technologies provides a new approach that synthesizes the advantages of each technology as well as overcomes the limitations. Hybrid EEG-fNIRS is one of the feasible methods of improving BCIs' performance. It simultaneously measures from both electrical and hemodynamic activity on the cerebral cortex, which may provide more detailed brainwave information in nearly real time by combining their features. This multimodality provides a novel processing approach to expand existing BCI applications.

EEG records electrical activities in the brain from electrodes placed on the scalp [5]. Because of its high temporal resolution, convenient wearability and low cost, EEG has been considered as the most actively used research tool in BCI. However, the low spatial resolution limits the EEG to record functionalities of brain which cannot accurately locate associated cortical sources [6]. To further enhance the performance of BCIs, hybrid EEG/fNIRS was proposed. In contrast to EEG, fNIRS uses near-infrared-range light to measure the concentration change of oxy- and deoxy-genated hemoglobin (HbO and HbR) and is not suspectable to electrical noise. The main limitation of fNIRS is the long response lag because the hemodynamic response requires time to reach its maximum amplitude, which means that the measurement cannot be used in real-time applications [7]. Although hybrid EEG-fNIRS is considered to combine the advantages of EEG and fNIRS in a way that compensates for the limitations of each modality, the possibilities of using hybrid EEG-fNIRS to discriminate specific cerebral activity features are not investigated comprehensively. There are two problems of addressing the current state of arts in hybrid EEG-fNIRS applications in BCIs.

One main challenge is determining an organized structure to categorize hybrid EEG-fNIRS systems in BCIs. Since the role of fNIRS in each BCI system can vary, such as complements to achieve the same goal as

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EEG or to perform independent duties in the same experiment. Because of the various proposals for the EEG-fNIRS combination, there are no simple categories that can explain the roles and operations in different lines of research. Another issue is the complexity of determining the usability of hybrid EEG-fNIRS applications in BCIs. As a developing methodology in BCI related research, the efficacy of additional communication channels and external features can be influenced by channel locations, user abilities and other different variables. Therefore, it is difficult to determine the efficiency of different hybrid EEG-fNIRS structures across these various applications. To comprehensively examine the efficiency of hybrid EEG-fNIRS, various data analysis algorithms have been developed to analyze patterns from EEG/fNIRS data [8]. Machine learning algorithms, which are widely used in brain signal analysis, have been developed as effective tools for compensating the high variability in EEG analysis [9]. However, the usability of machine learning algorithms in EEG-fNIRS analysis is still in an early stage.

This paper mainly discusses the hybrid EEG-fNIRS from usability, integration of structure and algorithms perspectives to evaluate and represent the state of the art and its limitations.

2. Methodology

A systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol [10] and the Problem, Intervention, Comparison, and Outcomes (PICO) statement [11]. The flow diagram of PRISMA with results in each categorization section is shown in Fig. 1. As shown, the protocol for research here included three main iterative steps: (1) Initial Search: investigated related studies based on the keyword combinations in selected databases. (2) Prescreening: selected articles based on their titles and abstracts using the designed criteria. (3) Qualifying: read through the full text of the selected articles to make sure they are qualified.

2.1. Search strategy

The acquisition of relevant papers that used or studied an EEG-fNIRS hybridization was conducted on PubMed, Scopus and Web of Science as the literature collection source base. The selected articles were covered from the first published study utilizing hybrid EEG-fNIRS application in BCI to the most recent. Only full text articles written by English were included. Other publication forms, such as proceeding papers, unpublished working papers, dissertations, newspapers and books etc. are excluded. The keyword combinations of related studies focusing on analyzing the usability of different applications and the integration of EEG-fNIRS' structures and algorithms used in this paper is shown as Table 1. Using a combination of all the keywords resulted in 765 articles in the initial search.

2.2. Prescreening and qualifying criteria

The prescreening criteria are based on the titles and abstracts in the database. First, duplicated articles under different titles are removed. Then, articles were excluded if they 1) had no hybridization of EEG and fNIRS in physical set up or feature analysis; and 2) had no information about the analysis of populations, interventions, comparisons, outcomes, and study design. After prescreening and excluding duplicates, 147 papers remained.

The articles were then subjectively screened by authors to qualify the conformity and correspondence with the remaining studies. In the qualifying process, 6 studies that researched or incorporated EEG and NIRS were excluded because the near-infrared spectroscopy data were used for applications other than BCI. 12 studies compared the performances of EEG, fNIRS, and EEG-fNIRS together to determine if EEG-fNIRS was worth hybridizing. Such hybrid systems will be dubbed as "EEG-fNIRS" in this review. 5 studies compared the performances of EEG, fNIRS, EEG-fNIRS, and a fourth modality to measure differences in performance between EEG-fNIRS and other configurations, such as transcranial alternating current stimulation (tACS). The information from these studies was only confined to the EEG and fNIRS portion.

Table 1
Keyword Combinations for EEG-fNIRS Study Selection.

1	"BCI" AND "fNIRS" AND "EEG"
2	"BMI" AND "fNIRS" AND "EEG"
3	"Hybrid" AND "fNIRS" AND "EEG"
4	"Combined" AND "fNIRS" AND "EEG"
5	"Modalities" AND "EEG" AND "fNIRS"
6	"Strategy" AND "EEG" AND "fNIRS"
7	("ML" OR "DL") AND "EEG" AND "fNIRS"

(Abbreviation used as BCI = "Brain Computer Interface", BMI = "Brain Machine Interface", ML = "Machine Learning", DL = "Deep Learning", fNIRS = "functional Near-Infrared Spectroscopy", and EEG = "Electroencephalography". Search was done using both the abbreviations and the full names of the key words.).

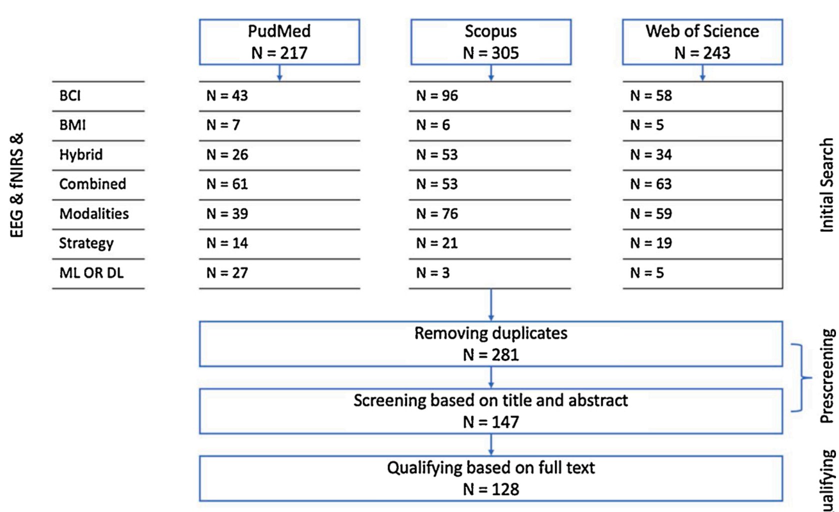

Fig. 1. PRISMA flow diagram for the initial study selection. (Abbreviation used as ML = "Machine Learning", DL = "Deep Learning", fNIRS = "functional Near-Infrared Spectroscopy", and EEG = "Electroencephalography".).

3. Results

After qualifying screening, 128 studies for this review were extracted from the initial 765 candidates. The 128 remaining studies were utilized to investigate the features of the hybridization of EEG-fNIRS in usability, integration of structures and algorithms, their limitations and future research directions.

As shown in Table 2, six categories of hybrid EEG-fNIRS tasks were selected based on the remaining papers. Mental tasks include studies that classify several mental states, such as workload, fatigue, and alertness, which can be reliably distinguished by recognizing patterns in EEG and fNIRS features. Emotion measurement tasks are studies that identify specific emotional states, such as sympathy, valence/arousal, and social rankings from EEG and fNIRS features. Motor control tasks include experiments which utilize the higher performance of hybrid EEG-fNIRS to further distinguish BCI-based motor control, such as sensorimotor rhythms. Perception tasks consist of studies aimed at distinguishing various biomarkers of perception including visual-spatial attention, auditory attention and olfactory attention. Cognitive evaluation and rehabilitation tasks include studies that use hybrid EEG-fNIRS systems for evaluation and rehabilitation training purposes in the context of mental diseases or disabilities. Cognitive improvement tasks refer to studies aimed at improving general human cognitive abilities.

To evaluate and determine the system integration, usability and analysis algorithms of hybrid EEG-fNIRS in BCI applications, remaining studies were categorized based on the general characteristics regarding: stimulus modalities, task types, measured cortical regions (EEG and fNIRS), and role of operations to differentiate the integrated functions of hybrid EEG-fNIRS as simultaneous or sequential. The resulting features of the hybrid EEG-fNIRS studies are shown in detail in Table 3. The stimulus modalities and task types categories demonstrate the range of tasks utilized in hybrid EEG-fNIRS studies. Monitored cortical regions of EEG and fNIRS and role of operations categories are used to analyze the integration of designing EEG-fNIRS hybridization strategies in different BCI applications. The information in each categorization is presented in Tables 4 and 5 correspondingly. The modalities associated with BCI applications in the remaining hybrid EEG-fNIRS related studies are represented in Table 4. To evaluate the integration of hybrid EEG-fNIRS, Table 5 shows the regions of cortex that EEG and fNIRS detected and whether they cooperated for the same goal or had decentralized duties.

Table 6 shows the state of art of machine learning algorithms in EEG-fNIRS and their performance in terms of classification. The classification algorithms include various machine learning methods and their ensemble learning methods. The result of Table 6 demonstrates the methodology of normalized feature generalization and their corresponding performance according to different neural network architectures. As a comparison, the accuracies of different studies are presented to evaluate their performances. The advantages of each algorithm depend on their dominances in the purpose of architecture design.

4. Discussion

4.1. Combined EEG-fNIRS applications

As shown in Table 3, mental task is the most studied topic, comprising 32.8% of selected studies. As a relatively new BCI technology, EEG-fNIRS has become a popular approach since it provides higher accuracy in decoding brain activities with less electrical noise in specific cortex regions. However, the mental status, such as fatigue [128] and alertness [129], has been considered as a synchronization of multiple regions. Analyzing one or few cortex regions with higher accuracy may not be able to provide more information. Several studies [12,13,21,56,76] showed that mental tasks using EEG-fNIRS signals achieve comparable classification performance with those using EEG signals, indicating the need for advanced algorithms on EEG-fNIRS signal analysis and fusion. According to the result from contained studies related to mental tasks, proposed applications of using mental status change as the indicator are involved in driving status monitoring [17,20,29] and user engagement measurement [28].

Table 2
Proportions of using hybrid EEG-fNIRS in different BCI tasks.

Task Categories	References	Count	Percentage
Mental tasks	[12–32]	21	32.8%
Emotion measurement task	[33–38]	6	9.4%
Motor Control Task	[39–53]	15	23.4%
Perception Task	[54–62]	9	14.1%
Clinical Evaluation & Rehabilitation Task	[63–70]	8	12.5%
Cognitive improvement Task	[71–75]	5	7.8%

Table 3
Categorization Details of Relative Hybrid EEG-fNIRS Studies.

Stimulus modalities:	Visual, auditory, operant, workload, olfactory and external stimulus
Task types:	Active and passive tasks
Detected cortex regions (EEG):	Prefrontal, motor, temporal, occipital, visual/auditory, whole head
Detected cortex regions (fNIRS):	Prefrontal, motor, temporal, occipital, visual/auditory, whole head
Role of operations:	Simultaneous and sequential

Table 4
Applications of each modalities in hybrid EEG-fNIRS.

Applications	Stimulus Modalities	Mental Tasks	Reference
Mental workload	Workload	Passive	[12–14,17,19,20–22,25,30,32,60]
	Visual	Passive	[26,31]
Math ability	Workload	Passive	[15,18]
ALS	Visual	Passive	[65,68]
ADRD	Verbal	Passive	[63]
ADHD	Operant	Active	[66]
	Verbal	Active	[67]
Novel clinical applications	Visual	Passive	[61,76]
	Verbal		[23]
	N/A		[40,69]
Emotion perception	Verbal	Passive	[33]
	Visual		[34–38]
Epilepsy	Operant	Passive	[64,70,77–83]
		N/A	[81]
Facial recognition	Visual	Passive	[55,84]
Language reorganization	Verbal	Passive	[85,86]
Motor control	Operant	Active	[39,41,43,44,46,50–53]
		Passive	[35,42,47,49]
Measurement system design	Visual	Passive	[87–89]
	Workload	Passive	[90,91]
	Operant	Active	[45]
		Passive	[44,92]
	N/A	N/A	[93]
Sedation	Workload	Passive	[24]
Signal classification	Operant	Active	[94–97]
		Passive	[72,98–101]
	Workload	Passive	[75,102,103]
	Visual	Passive	[59,104]
	Verbal	Active	[105]
Transcranial stimulation	External	Active	[71,106]
		Passive	[73]
Visual Stimulation	Visual	Active	[72]
		Passive	[58,107]
Visual Processing	Visual	Passive	[57,74]
Visual and Auditory Stimulus	Visual & Auditory	Passive	[54,108]
Olfactory Stimulus	Olfactory	Active	[56]

Abbreviation used as "ALS = "Amyotrophic Lateral Sclerosis", "ADRD" = "Alzheimer and related dementia".

Table 5
Applications of electrode/optodes selection in hybrid EEG-fNIRS experiments.

Applications	Electrodes regions	Optodes regions	Roles of operations	Studies
Mental workload	Occipital cortex	Occipital cortex	Simultaneous	[25]
	Prefrontal cortex	Whole head	Not Specified	[12]
	Prefrontal cortex	Prefrontal cortex	Not Specified	[13,60]
	Prefrontal cortex	Prefrontal cortex	Simultaneous	[14,21,22]
	Central cortex	Central cortex	Sequential	[49]
	Whole head	Central cortex	Simultaneous	[50]
	Occipital cortex	Prefrontal cortex	Simultaneous	[26]
Math ability	Prefrontal cortex	Not Specified	Simultaneous	[15]
ALS	Whole head	Prefrontal cortex	Simultaneous	[65,68]
ADRD	Frontal cortex	Whole head	Simultaneous	[99]
ADHD	Prefrontal cortex	Prefrontal cortex	Simultaneous	[66]
	Whole head	Prefrontal cortex	Simultaneous	[67]
Novel clinical applications	Prefrontal cortex	Whole head	Simultaneous	[76]
	Whole head	Whole head	Simultaneous	[23,40,61]
	Motor cortex	Motor cortex	Simultaneous	[69]
Emotion perception	Prefrontal cortex	Prefrontal cortex	Simultaneous	[34]
	Left hemisphere	Whole head	Simultaneous	[36]
	Prefrontal cortex	Whole head	Simultaneous	[37]
	Central cortex	Central cortex	Simultaneous	[38]
Epilepsy	Temporal cortex	Temporal cortex	Simultaneous	[64]
	Central cortex	Central cortex	Simultaneous	[70,77]
	Frontal cortex	Frontal cortex	Simultaneous	[79]
Facial recognition	Temporal cortex	Temporal cortex	Not Specified	[55,84]
	Whole head	Prefrontal cortex	Simultaneous	[69]
Language reorganization	Whole head	Temporal cortex	Simultaneous	[86]
Motor control	Whole head	Motor cortex	Simultaneous	[41]
	Motor cortex	Whole head	Simultaneous	[42]
	Central cortex	Whole head	Sequential	[46]
	Prefrontal cortex	Prefrontal cortex	Sequential	[43]
	Whole head	Whole head	Simultaneous	[44]
	Motor cortex	Motor cortex	Simultaneous	[39]
	Whole head	Central cortex	Simultaneous	[51,53,109]
	Central cortex	Prefrontal cortex	Simultaneous	[52]
Measurement system design	Motor cortex	Motor cortex	Simultaneous	[87]
	Whole head	Whole head	Simultaneous	[90,91,93]
	Temporal cortex	Temporal cortex	Simultaneous	[92]
	Whole head	Left hemisphere	Not Specified	[45]
	Whole head	Prefrontal cortex	Simultaneous	[89]
Sedation	Frontal cortex	Frontal cortex	Simultaneous	[24]
	Whole head	Whole head	Simultaneous	[94,96]
Signal classification	Motor cortex	Motor cortex	Simultaneous	[99]
	Prefrontal cortex	Prefrontal cortex	Simultaneous	[101,103,104]
	Occipital cortex	No details	Simultaneous	[59]
	Whole head	Central cortex	Simultaneous	[105]
Transcranial stimulation	Motor cortex	Motor cortex	Not Specified	[71]
	Prefrontal cortex	Prefrontal cortex	Simultaneous	[106]
Visual Stimulation	Whole head	Whole head	Simultaneous	[72]
	Occipital cortex	Occipital cortex	Simultaneous	[58,107]
Visual Processing	Occipital cortex	Occipital cortex	Simultaneous	[57,74]
Visual/Auditory Stimulus	Occipital cortex	Occipital cortex	Simultaneous	[54]
	Whole head	Whole head	Simultaneous	[108]

Abbreviation used as “ALS = “Amyotrophic Lateral Sclerosis”, “ADRD” = “Alzheimer disease and related dementia”.

Motion control also contains high proportion of selected studies with 23.4%. Motion control studies can be categorized into active tasks [42–44,47,50,51] and passive tasks [41,45,46,48–50]. In these tasks, hand motion is a dominated experiment setting in classifying motor imagery commands and differentiating actual hand movements. Compared with mental and motor control tasks, there are fewer applications of hybrid EEG-fNIRS in other tasks, especially for clinical tasks. This limitation is probably due to insufficient classification approaches in emphasizing the advantages of fNIRS in the analysis of diseases or disabilities.

Emotion measurement tasks and motor control tasks utilizing hybrid EEG-fNIRS provided significant improvement in extracting features from brain activities [28,42,45,60,130,131]. Because of the limitation of experiment settings, compared with other tasks, emotion measurement and motor control tasks require relatively longer period in each trial to measure corresponding cortical activations. The relative longer time in measurement may weaken the influence from fNIRS signal’s delay. Previous studies of motor control tasks found that the delay of fNIRS may cause the growth of moving artifact of remote-control devices. Future BCI-devices may consider to use supplemental signals such as Electromyography (EMG) to help to reduce artifacts in EEG-fNIRS measurements [41].

Unlike other tasks, measurements during perception tasks were limited by the structure of related cortex. Occipital cortex is mainly considered as the corresponding regions of visual, spatial, and relative attentions which is often decoded in perception classifications. A few studies on visual perception showed that adding fNIRS signals measured from the same region as EEG does not lead to significant improvement on the performance of BCI signal analysis [54,55,59,64]. It is hypothesized that EEG signal is good enough to distinguish brain evoked states on associated region of interest, such as occipital cortex [132]. Experiment designs compatible for hybrid EEG-fNIRS are required for further study in perception analysis, especially on maximizing fNIRS function in the analysis.

In Table 4, it is important to observe that most of the studies were designed as passive mental tasks. The reason is assumed that, in the state-of-art of hybrid EEG-fNIRS measure, the primary goal is classifying relative cognitive states with combined EEG-fNIRS features. According to stimulus modalities listed in the table, visual, operant and workload stimulus dominate the proportions. Moreover, except in specific applications (math abilities, mental workload), which have explicit research purposes on defining mental responses in different mental states, most studies still use traditional tasks such as n-back or motor imagery to

Table 6
The state of art of machine learning algorithms in EEG-fNIRS.

Classification	Neural Network Architecture	Features	Performance	References
Classic Machine Learning	SVM LDA	1) much simpler to train 2) easier to find a robust model.	Focus on relatively small data sets	[110–115] [94, 116–120]
DNN	DNN	Training these deep architectures is complicated, as the process gets slower the more layers are	EEG: accuracy of about 80% [121] fNIRS: accuracy of 94% [121]	[116,121]
RNN (temporal)	LSTM RNN	Input data are transformed into a 3-D tensor with standard dimensions of an LSTM-RNN.	Accuracy to 98.2% [122]	[123,124] [122]
CNN (spatial)	Convolutional Neural Networks (CNNs)	Implementation of neural networks where neurons are connected to portions of signals and or images that are close in time and/or space	An accuracy ranging between 96.9% and 100% [125]	[125]
SNN	SNN	using trains of spikes (binary temporal events) transmitted among spatially located synapses and neurons [126]	Outperformance SVM by 11% [126]	[126]
Ensemble learning	SVM + LDA	To verify the efficacy of LDA classifier, RLDA classifier was used as a weak learner [127]	significant increases in the bitrate and accuracy [127]	[127]

evaluate the performance of the hybridization of EEG-fNIRS in exploiting more functions. It may provide a new approach in regulating the efficient measurement in determining the EEG-fNIRS performance by developing more suitable stimulus using EEG-fNIRS according to its high spatial resolution on cortical regions.

According to the result from Table 5, most of the studies used simultaneous EEG-fNIRS to demonstrate feasibility in further research. After counting the number of detected cortex regions for both EEG and fNIRS, the distribution of different regions in both EEG and fNIRS are approximately even when used in the same application. From the observation, it is hypothesized that the node arrangement of combining EEG and fNIRS is still unclarified and the arrangement may be one of the constraints of improving its performance. Thus, one avenue for future research is comparing hybrid EEG-fNIRS performance with various arrangements. It is also interesting to see the arrangement of optodes and electrodes are disparate between the attention on optimizing system processing and measuring specific brain activations. On the purpose of developing system processing, optodes and electrodes are mainly located in the same regions. To emphasize the weights of experimental related cortex regions in measuring, electrodes are primarily used to measure event-related desynchronizations (ERD) from brain oscillatory as well as optodes which set on the implicated cortex regions to accentuate the signal on these regions.

4.2. Machine learning algorithms in EEG-fNIRS

Multimodal EEG-fNIRS data can provide superior performance metrics, and different classification procedures have been applied to combined EEG-fNIRS BCI [94,110–112,114–121,123–126,133–143]. Specifically, by employing support vector machine (SVM) [110–115] or linear discriminant analysis (LDA) [94,116–120] (which are as the classic machine learning methods), the BCI signals have been classified by EEG power spectral densities and fNIRS signal amplitudes. Furthermore, linear discriminant analysis ensemble classifiers have been employed in [127], to increase the bitrate as well as the classification accuracy for fNIRS-BCI datasets. The advantages of the classic learning methods are that they are simple to train and easy to find a good robust model. However, the computational cost would grow linearly with the size of the data set, which implies that the aforementioned methods are suitable for relatively small data sets with fewer outliers.

For the complex non-linear transformations-classifications, Deep Neural Networks (DNN) have been applied [116,121]. By employing few EEG recording channels via DNN, an average accuracy of about 80% can be achieved [121]; while regarding fNIRS, classified mental tasks through DNN can achieve an accuracy of 94% [121]. Moreover, DNN can neither provide memory capabilities or sequential information control nor encode the spatio-temporal information [138], multiple technological developments have been allowed for deep learning evolution, e.g., either developing the neural networks where outputs are fed back into the network in a sequential manner by recurrent neural networks (RNNs) with sensitivity and specificity of 89.7% and 95.5% respectively [122–124], or encoding temporal and/or spatial information standard by convolutional neural networks (CNN) to achieve an accuracy ranging between 96.9% and 100% [125]. In addition, considering the brain functions as a spatio-temporal information processing machine, Spiking Neural Network (SNN) has been introduced to construct and train in an unsupervised mode with a recurrent 3D SNN reservoir, to learn the spike sequences. In [126], the performance of SNN can outperformance SVM by 11%.

4.3. Prospects for future research

Based on the 128 selected articles, the correlation between EEG and fNIRS signals are not fully understood and the challenge of combining the advantages of electrical and optical measurements still maintains. To promote the innovation of EEG/fNIRS applications on the purpose of maximizing the advantages of combination, more future research is needed to explore possible applications, integrations, and algorithms in EEG/fNIRS analysis. The majority of selected studies appropriates EEG-fNIRS by combining collected electrical and optical handcrafted features for classification purpose. In some recent studies, machine learning algorithms play significant roles in integrating features extracted from EEG and fNIRS into multidimensional feature vectors, but the advantages of spatial information on local regions from fNIRS and temporal information on whole head from EEG were not emphasized. Furthermore, as a starting stage technology, combined EEG/fNIRS does not have uniform, standardized procedure due to many different methods regarding signal processing and analysis which makes the comparability and interpretation difficult. Therefore, effective research methods for comparison and interpretation can be further pursued in the next step. Splitting measured cortical functions may provide unique approaches to emphasize the spatial performance from fNIRS as well as temporal performance from EEG which is also convenient in comparison and interpretation.

The advantages of EEG's temporal resolution can be utilized by measuring oscillatory correlates (ERP or ERD/ERS) from whole head to detect brain evoked potentials. Because of fNIRS high spatial resolution, optodes can be set on the local region, such as occipital or prefrontal regions to measure significant attentional or visual processes. Previous studies have demonstrated the correlation between cortical connectivity and sensory processing in different mental states [144,145]. In this case, using combined EEG-fNIRS may provide a possibility in the study of measuring complex information processing between different cortex, such as driving, language or mental disease evaluation processes. Compared with fMRI which is the main device has been used in measuring cortical connectivity, combined EEG-fNIRS may be able to implement a portable experimental environment for expanding more studies.

5. Conclusion

This article presents a systematic review of studies evaluating the usability and designing of hybrid EEG-fNIRS in different applications of BCIs. The overall results demonstrates that the application of combined EEG-fNIRS is still in an early stage and suggest that it may be potentially beneficial in improving the algorithms and physical system designing of hybrid EEG-fNIRS in the near future, such as emphasizing spatial and temporal advantages from fNIRS and EEG accordingly by designing advanced feature extraction methodologies and splitting nodes in different targeted cortical functions. Moreover, it is necessary to continue developing more possible applications with hybrid EEG-fNIRS, especially for complex information processing related fields.

Since the research in EEG-fNIRS is relatively new, the number of studies included in this review is relatively small. Studies were selected from the first published study utilizing hybrid EEG-fNIRS recording in BCI related applications to the most recent to maximize the quantity of studies to analyze. However, some of these studies may not be able to represent the state of art in the hybridization of EEG and fNIRS. These studies were cited as references, but not the direct evidence in observations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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