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A novel approach for communicating with patients suffering from completely locked-in-syndrome (CLIS) via thoughts: Brain computer interface system using EEG signals and artificial intelligence

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This work is dedicated to all MND patients and to the late Mr. Naeem Radwan who was the inspiration for this research work and who sadly passed away suffering from MND in Nottingham in 2019, aged 39

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ABSTRACT

This paper investigates the development of an intelligent system method to address completely locked-in-syndrome (CLIS) that is caused by some illnesses such as Amyotrophic Lateral Sclerosis (ALS) as the most predominant type of Motor Neuron Disease (MND). In the last stages of ALS and despite the limitations in body movements, patients however will have a fully functional brain and cognitive capabilities and able to feel pain but fail to communicate. This paper aims to address the CLIS problem by utilizing EEG signals that human brain generates when thinking about a specific feeling or imagination as a way to communicate. The aim is to develop a low-cost and affordable system for patients to use to communicate with carers and family members. In this paper, the novel implementation of the ASPS (Automated Sensor and Signal Processing Selection) approach for feature extraction of EEG is presented to select the most suitable Sensory Characteristic Features (SCFs) to detect human thoughts and imaginations. Artificial Neural Networks (ANN) are used to verify the results. The findings show that EEG signals are able to capture imagination information that can be used as a means of communication; and the ASPS approach allows the selection of the most important features for reliable communication. This paper explains the implementation and validation of ASPS approach in brain signal classification for bespoke arrangement. Hence, future work will present the results of relatively high number of volunteers, sensors and signal processing methods.

1. Introduction

Brain Computer Interface (BCI) applications provide the means for people especially with physical disabilities to communicate with others through brain signals [1–3]. People with various physical disabilities and MND (ALS) may lose the ability to move their muscles including in some cases their eyes. However, these disabilities often do not affect other cognitive brain functions such as thinking and imagining [4]. Hence, patients in advanced stages of MND may produce spontaneous electrical signals with their thought process. Study reveals that people with such disabilities have emotions and feelings that can be recognisable through brain signals [5–7]. EEG is a technique obtaining continuous brain wave patterns and becoming one of the most advantageous systems over other available techniques in terms of temporal resolution, invasiveness, portability and cost [8,9]. EEG contributes in both medical diagnosis and biomedical engineering research field in many ways [10] and therefore, greatly supports BCI advancements. People with ALS can communicate through limited number of technological arrangements, among them eye activity-based (for example, eye gaze), and cognitive activity-based (for example, P300 BCI) systems are commonly used [11]. From a comparison study between those two systems for ALS patient, [11] found that BCI is most controllable and comfortable system. Some patients feel eye-tracking is a stressful system due to frequent eye movements, prolonged eye focus to a particular direction and wearing head mounted eye tracking interface. Moreover, the controllable command is not feasible to use in sleeping posture. On the other hand, there is no such restriction for BCI and it is easier with minimum temporal demand. Among steps in BCI development, feature extraction and selection are significantly performed to measure the major structural components within the signal [12] and these are essential for brain signal classification performance [13].

Several brain signal processing techniques have been used for feature extraction to transform the signals into time and/or fre-

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quency domain. Among them, Fast Fourier Transform (FFT) which extracts the characteristics features from frequency domain, is widely used techniques [14–19]. Choosing the best feature extraction method appropriate for a particular application remains a continuing challenge [20,21]. Rather, it is more target oriented based on the functionality of ultimate application. Researchers mostly choose separate techniques for feature extraction and optimisation among potential choices which consume time and effort. A novel concept named ASPS has been introduced by [22] to address the dilemma in terms of sensory signals and achieved an intense solution for extracting and selecting feature automatically. The approach is developed on the basis of Taguchi's orthogonal arrays and initially implemented on condition monitoring of machining process. In this research work, we aim to apply and determine the capability of novel ASPS approach in the field of EEG based sensor signals to extract relevant features for recognising imaginations.

Another step is brain signal analysis is based on extracted features which enables brain signals to be operated as control commands for further applications [20,23]. Making a choice of classifier among diverse range of classification and regression algorithms is another challenge since it is dependent on the nature of sensory signals and classifiers. Some prevailing classifiers include, support vector machine, Naïve Bayes classifier, KNN, ANN etc. which achieve impressive performance in brain signal classification [24,25]. Among numerous classifiers, ANN such as Feed forward neural network (FFNN) or Multi-layer perceptron (MLP) [13,26] and LVQ [27,28] have been adequate for specific purposes.

The focus of this study is on the selection of the most suitable sensor characteristic features (SCFs) that allows identifying the thoughts and to be linked to a specific computer action or related to answering a specific question. The ultimate aim of the study is to discover the sensor locations, signal components and analysis methods that will be optimal for a low-cost communication system for patients. The ASPS approach helps to extract the optimised features and verify the results to recognise the imaginations from EEG brain signals using ANN. This research work contributes to the state-of-the-art in brain signal processing field in three ways: 1) a demonstration of ASPS approach applied for 3 sensors EEG-based brain signals with bespoke experiment; and 2) an integration of other signal processing techniques that work for time and frequency domains together; and 3) an implementation of extracting sensitive features to recognise the imagination accurately. This paper intentionally simplifies the number of sensors and signal processing methods to explain the method in detail. Future work will include the full capabilities of the approach, but will depend on this paper to explain the detailed steps of the methodology for the readers.

This paper is organised as follows: Section 2 reviews the literature of relative brain signal processing methods, Section 3 outlines the experimental methodology for implementing ASPS approach in brain signals, Section 4 discusses the analysis of results with verification and Section 5 concludes with novel accomplishment of ASPS approach and scope of further study.

2. Related work

BCI development attracts significant attentions to assist the people with physical limitations. Significant applications based on brain signals have been evolved in various domains, inter alia emotion detection [5,6,29–33], speech translation [34,35], text conversion [36]. A research work presented in [37] infers that there is a high demand for developing BCI for specific applications such as direct personal communication, private conversation and general computer use. The reference presented 28 patients with locked-in syndrome; one of the outcomes from that research indicates that 96% individuals use EEG signals for such applications.

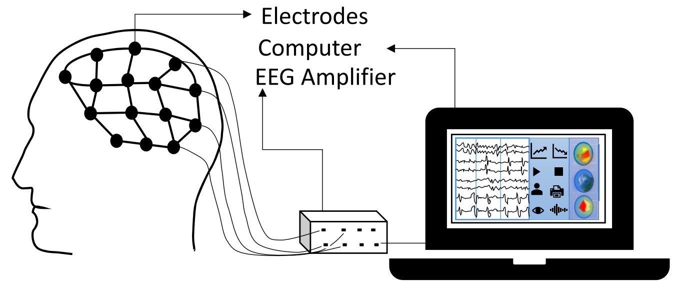


Fig. 1. A schematic diagram of an EEG system.

EEG signals are widely classified into five categories depending on their characteristics frequency band: delta (δ, frequency range 0–4 Hz), theta (θ, frequency range 4–8 Hz), alpha (α, frequency range 8–12 Hz), beta (β, frequency range 12–30 Hz), and gamma (γ, frequency range 30–100 Hz); where the power in each band is modulated by the subject's physical behaviours, feelings and mental states [38,39]. EEG directly measures brain's electrical activities with few milliseconds' temporal resolution. Certain electrodes (see Fig. 1) are placed across the scalp to determine the amplitude of electrical impulses between presynaptic and postsynaptic neurons. With the advancement of technology, emergency EEG system (eEEG) and wireless microEEG systems are designed by [40] and [41] respectively which are able to extract the brain waves rapidly in emergency departments or in ICU for patients' care and EEG laboratory. Using EEG hyperscanning device, brain signals can be captured simultaneously from multiple subjects which are also useful for non-verbal communication [42].

After EEG acquisition, brain signals are processed, analysed and classified using several methods and algorithms towards specific applications development [23,43,44]. In the field of feature extraction and selection, time and/or frequency and space-time-frequency domain analysis can extract signal characteristics with various accuracy [45,46,3]. For the development of Brain Computer Interface BCI, reference [23] presents some of the potential methods for feature extraction and selection namely: FFT, Short Term Fourier Transform, Auto Regressive Model Wavelet Transform (WT), Wavelet Packet Decomposition, Common Spatial Pattern etc. Among them, a few studies compared between multiple techniques though there is no one can be said as appropriate for all purposes since every technique has pros and cons depending on some parameters. To address the proper choice of signal processing technique depending on desired purpose [22] innovated ASPS approach as a novel idea which minimises experimental work, time and cost. The ASPS approach is theoretically simple and convenient to apply for useful information extraction from multiple sensory signals. Later other novel accomplishments have been executed using ASPS approach undertaken by [47–49] to efficiently determine the key features as well as the sensor in terms of condition monitoring of gearbox, tool and water leakage detection system respectively. The rationales for using ASPS here are:

I. It is a systematic and compact approach of signal processing method where implementation of an algorithm can take over the whole process automatically rather than separate application of multiple methods.
II. It eventually determines the best suitable signal processing technique along with associated features.
III. A feasible method since it reduces cost, minimises time, moderates methodological steps and optimises the internal complexity.
IV. A novel implementation in terms of brain signal processing system.

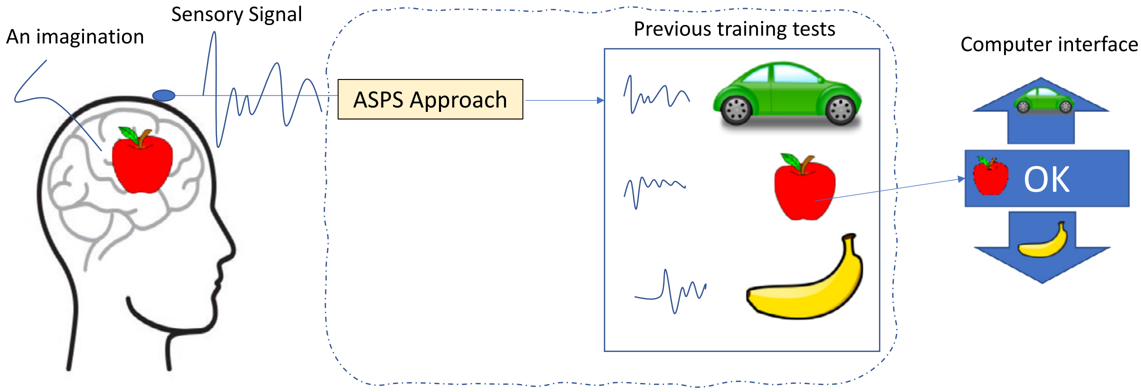


Fig. 2. The concept of reading thoughts for computer interface using the ASPS approach.

Machine learning with both supervised and unsupervised techniques have been applied for brain signal classification in last two decades. Machine learning, a subclass of artificial intelligence that confers various algorithms and statistical models, and trains computer to perform certain tasks autonomously [50]. EEG classification experiments with certain number of selected sensors are conducted in the state of the art along with numerous algorithms as well as potential architectures.

In literature, reference [27] classified four types of body movement tasks by experimenting with Learning vector quantisation (LVQ). In the experiment, EEG signals are collected for 17 sensors based on single trial data. Authors investigated the time and frequency components for before and after reaction stimulus for each task and their model can classify the movements with more than 70% accuracy. EEG signals are clustered by [28] using LVQ for five mental tasks of three subjects and attained diverse range of accuracy depending on datasets and subjects. Authors employed maximum entropy method with frequency analysis and examined the availability of features within alpha and beta frequency band. [51] conducted an experiment using six sensors-based EEG signals for five mental tasks initially with one subject. Three different signal processing methods, namely: Principal component analysis (PCA), FFT and WT, are separately applied for extracting features and each case of extracted features is applied through Back propagation neural network and support vector machine algorithms for signal recognition. Mental tasks are classified for various combination of signal processing technique and classification algorithm. The best performance of 84% accuracy is obtained by combining wavelet transformation-based features and support vector machine algorithm. Research with motor imagery classifications are exemplified many neural network algorithm and high performance can be achieved by ANN. Reference [26] conduct motor-imagery classification with multiple classifiers where MLP outperforms with 90% accuracy and lower training time over SVM, KNN, Random Forest, Naïve Bayes and Logistic regression. Comparing MLP and LVQ, [52,53] found that LVQ and MLP perform well for high dimensional and lower dimensional inputs respectively. Some studies are reviewed by [23,43] where other deep learning algorithms such as Recurrent neural network (RNN), Long short-term memory (LSTM), Convolutional neural network (CNN) achieve relatively reasonable accuracy [54–57] in terms of large dataset, time-series prediction or image processing. However, both MLP and LVQ techniques have comparable sensitivity in terms of smaller size of training data and MLP is a faster training process. Therefore, this research uses FFNN and LVQ algorithm to enhance the performance in relation to simplicity, rapidness and use of minimal computation resources.

From the literature review considerable research has been working on EEG signal processing for feature extraction and selection to achieve accurate signal classification. The selection of signal processing techniques is challenging to separately consider one or more techniques. There is little research found on considering combinational signal processing techniques within a standalone method. To address this difficult situation, we are aiming to investigate the ability of the ASPS to discriminate between multiple different mental imagery.

Fig. 3. A volunteer wearing the EEG cap.

3. The methodology

The methodology includes bespoke experimental work combined with the ASPS approach and the implementation of FFNN and LVQ neural networks in order to classify mental imagery and compare different ANN model performances.

Fig. 2 presents the key concept of the suggested methodology. The participant will be asked to think about a specific imagination that is captured via a sensory signal or more. Then the ASPS approach will be used to analyse the data to extract sensory characteristic features (SCFs) that then will help to categorise the imaginations and select the correlated SCF which can potentially be linked to a specific response or computer action.

3.1. Signal acquisition

EEG signal acquisition was processed by international 10–20 EEG [58] electrode placement system as shown in Fig. 3 where 3 sensory signals were selected with three random yet distant

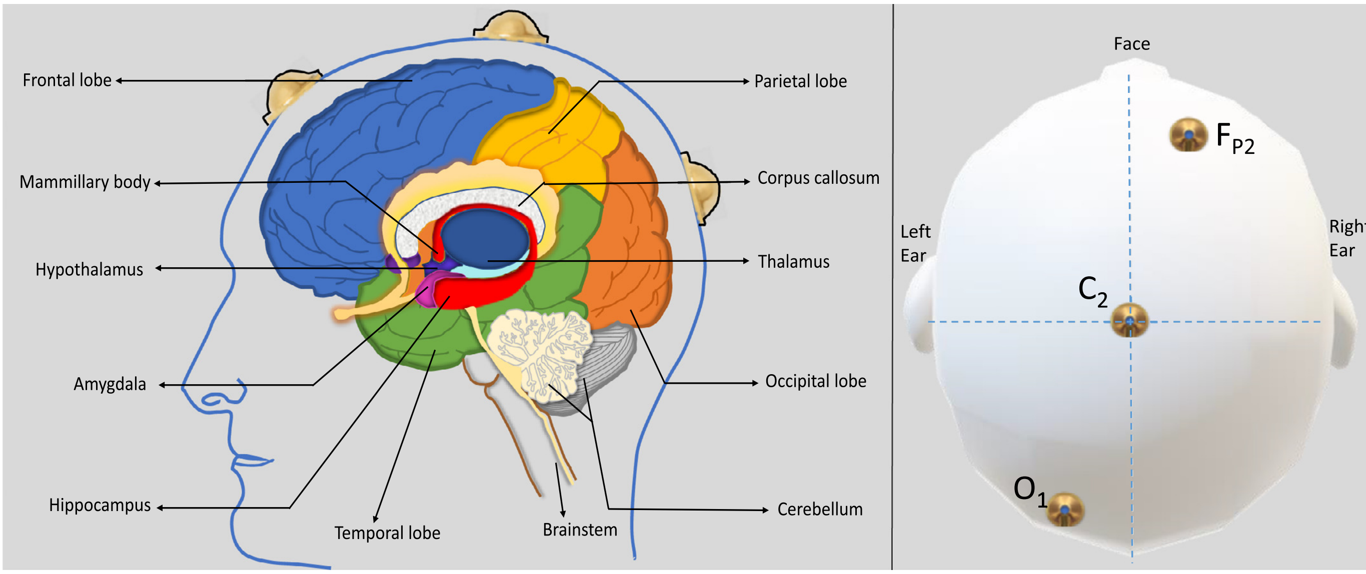


Fig. 4. Selected sensor names and locations (side and top view).

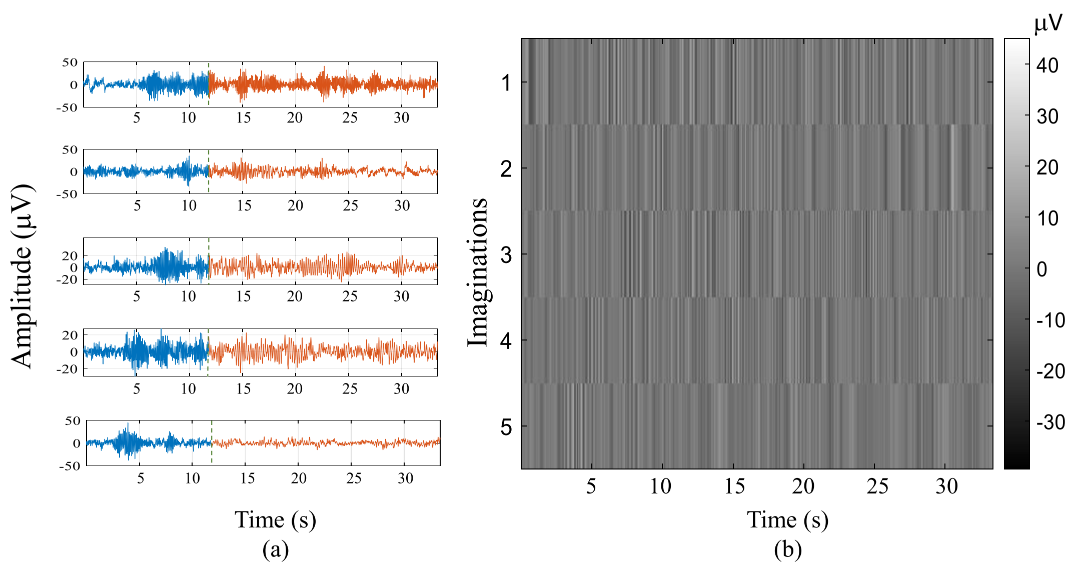


Fig. 5. Raw signals of 5 imaginations from one volunteer.

brain locations. Fig. 4 shows the selected sensor names and corresponding EEG cap location. The purpose of selecting three different brain locations is to explore the differential effects of signals from distant electrodes as they sample the activities of brain regions associated with different functions [38,59]. Consistent data are collected for 5 heterogeneous imaginations (see Table 1) with two subjects (one man and one woman) and two repetition of the experiments (A and B). A recorded audio stream was used for inviting various imaginations one after the other where each imagination had two parts: first, relaxation and then, a specific mental task of imagination. Fig. 5(a) illustrates the raw signals of relax and mental task for 5 imaginations which are plotted in Fig. 5(b) with grayscale map. Imaginations were arranged based on the variety of mental tasks that includes motor imagery, mental calculation, imagination of an object, smell, and motion with sensing the environment. The TMSi system is used for EEG recording with sampling frequency 2 kHz. After recording we extracted a combined relaxation and imagination signal for further analysis.

3.2. Signal processing using the ASPS approach

It is necessary to discover the intrinsic characteristics of sensory signals that represent the generated thoughts, if at all possible, through feature extraction technique that has high dependency on the desired goal. Exemplary, but limited in number, signal processing methods are selected in this work to test and explain the algorithm to enable the low-cost implementation via affordable microprocessor boards and to enable the reader to understand the suggested method. Using linear analysis in frequency and time-frequency domains a number of methods can be used for feature extraction of EEG signals [17]. We applied novel ASPS approach [22] to address the challenges in terms of brain sensory signals and examine whether the method is able to achieve an effective solution for extracting and selecting feature automatically.

The ASPS approach uses the “Black box” concept [22,60] where the relationship between the input and output parameters or variables is obtained to determine the status of the system (the black box). The ASPS approach has been adopted in this research work as a ‘Delta feature’, Δ, for measuring sensitive EEG SCFs. The delta

Table 1
List of imaginations that the volunteers are invited to imagine.

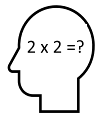
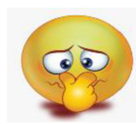
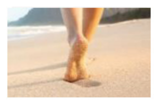
Number	Description	Imagination
1	Imagine an African Elephant	
2	Imagine kicking a football with left foot	
3	Calculate of 2×2 in your mind	
4	Smelling a rotten egg	
5	Imagine walking on a warm sandy beach	

Table 2
List of statistical functions used for this example.

Index	Definition	Equation
1	Mean	$E_1 = \frac{1}{n}\sum_{i=1}^{n} x_i$
2	STD	$E_2 = \sqrt{\frac{\sum_{i=1}^{n}(x_i - E_1)^2}{N}}$
3	Variance	$E_3 = \frac{\sum_{i=1}^{n}(x_i - E_1)^2}{N}$
4	Max	$E_4 = \max(x_i)$

feature, Δ can be obtained from the changes between relax and mental tasks (imaginations) as a part of the potential brain signals' frame. As such, higher differential will indicate more sensitive features with respect to a specific sensor. Delta feature values with all selected sensors are used to construct a matrix named the Association Matrix (ASM). Taguchi's orthogonal array can also be implemented within ASPS approach for determining the feature sensitivity and reducing the number of experimental works needed for the implementation of full factorial experimental testing [22].

In this work, three sensors simultaneously received the brain activity from subject's head with distant electrode positions (see Fig. 4). Four statistical functions have been considered (see Table 2) which are applied on both time domain and frequency domain (FFT output) of mental tasks and relax signals. The statistical functions are mean, standard deviation, variance and maximum.

There is no such number of features that can be said to be sufficient; rather it depends on the number which can characterise the required status effectively. For example when considering other methods in literature, reference [61] extracted three features and classified cursor movements with best accuracy at 88.75%. To detect obstructive sleep apnea from EEG signals, reference [62] considered 4 features and achieved 98% success using SVM classifier. For 5 categories of emotion classification [30] used 6 statistical functions as features and achieved accuracy at 95% with back propagation neural network. In this paper, the number of features selected are reduced to ensure a low-cost microprocessor board can be used to develop the product to be affordable to patients and their families. And also to simplify the method for the reader to enable the full understanding of the methodology, see Fig. 6.

Raw data is a time domain signal and FFT output contains all the decomposed frequency components of the raw signals where

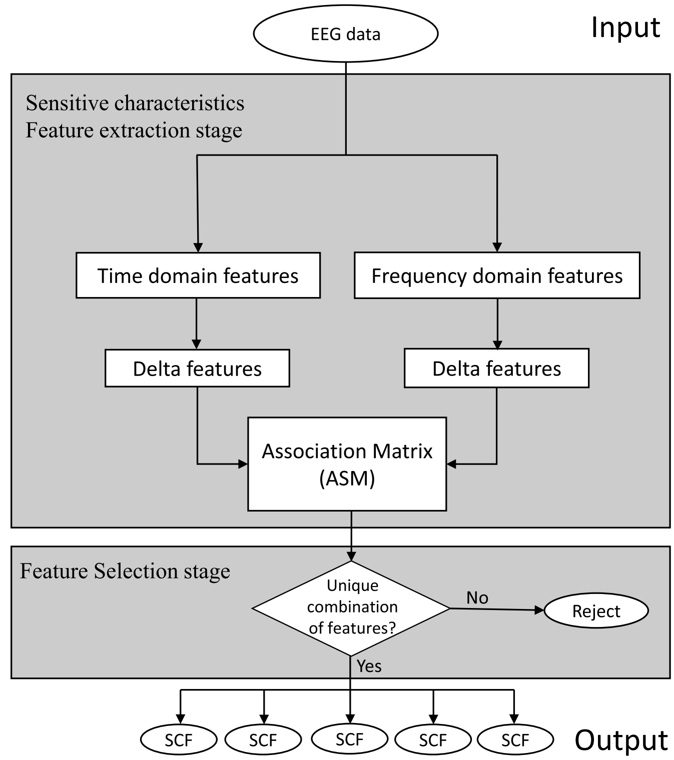


Fig. 6. The flowchart of methodology of the ASPS approach.

the relative strengths (i.e., magnitude) are measured. The significant part of FFT output is partitioned into two equal parts and the above-mentioned statistical functions are measured for each part. FFT output is calculated using Fast Fourier Transformation where the frequency space ($X(k)$) is transformed from the configuration space ($x(n)$) as presented in equations (1) and (2).

$$X(k) = \sum_{n=0}^{N-1} x(n) \cdot e^{-\frac{j2\pi kn}{N}}; \tag{1}$$

$$x(n) = \frac{1}{N}\sum_{n=0}^{N-1} X(k) \cdot e^{-\frac{j2\pi kn}{N}}; \tag{2}$$

where, $j = \sqrt{-1}$, $N =$ length of $x(n)$.

From the successive signals of relax and mental imagination task, normalised features are arranged for each imagination. The two segments of FFT (relax vs imagination) with four statistical functions generate eight values; and time domain signals with four features produce a total 12 values. The delta feature values are calculated from the difference between mental task features and relax features, which are organised in a matrix named the Association matrix (ASM), see Fig. 6. The ASM combines all time domain and frequency domain features. Therefore, the resultant sensory characteristics features represent sensitivity in an arranged format within the ASM. For n number of EEG sensors and m number of signal processing techniques including time domain and frequency domain, the ASM can be mathematically expressed as in equation (3):

$$\text{ASM} = \begin{bmatrix} f_{11} & f_{12} & f_{13} & \dots & f_{1m} \\ f_{21} & f_{21} & f_{21} & \dots & f_{2m} \\ \dots & \dots & \dots & \dots & \dots \\ f_{n1} & f_{n2} & f_{n3} & \dots & f_{nm} \end{bmatrix} = f_{xy}$$
$$\text{where } 1 \le x \le n \text{ and } 1 \le y \le m; \tag{3}$$

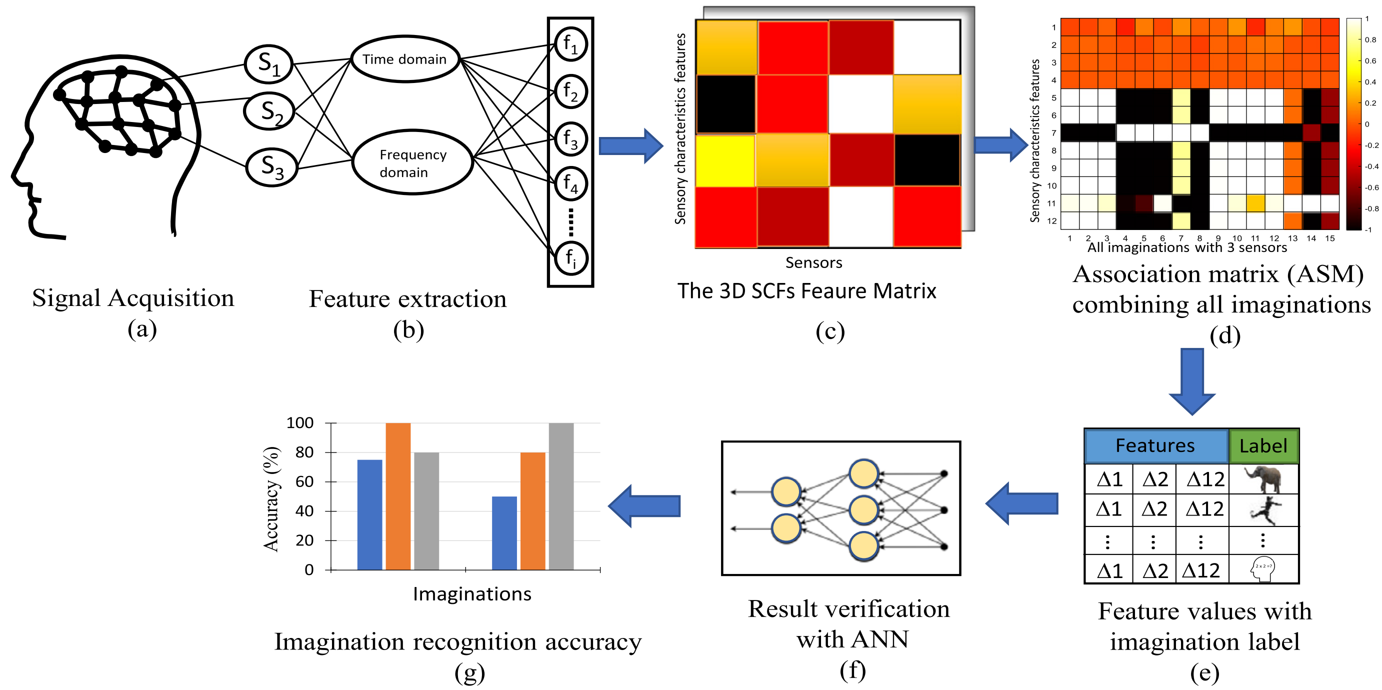


Fig. 7. Block diagram of the ASPS approach originally presented in [22]; which has been adopted for the brain signals application.

where f_{ij} is the SCF of the ith sensor and jth signal processing method.

As a result, an ASM can be created where each element of f_{ij} represents the dependency coefficient. Fig. 6 shows the flowchart for the methodology of ASPS approach which is followed in this research. The concept of the ASPS approach can utilise more signal processing techniques for creating the Association matrix. The extracted features from the ASM are required to verify the performance for recognising imaginations. The block diagram of ASPS approach in brain signal experiment is illustrated with Fig. 7. In this experimental work, we processed the total 12 delta features on each imagination for two subjects with two experiments and verified the selected features in further steps. As described in Fig. 7, the sensors and the signal processing methods are used to extract SCFs (Sensory Characteristic Features) and arranged in a 3D matrix, Fig. 7(c). The change in value between relax status and imaginations status (Δ) is used to construct the Association Matrix (ASM), Fig. 7(d). Then sensitive SCFs from the ASM are ranked and the most sensitive ones are selected, Fig. 7(e). However, it is worth mentioning that unlike previous applications of the ASPS approach, this unique application requires unique patterns of SCFs change (from relax to imagination), to identify a unique status. Hence, insensitive features could still be a valid indication to characterise a specific status or imagination. Then AI systems such as neural networks (Fig. 7(f)) will be used to test the viability of the data in recognising the imaginations, Fig. 7(g). Fig. 8 presents an example of the time domain and frequency domain feature extraction from the raw EEG data. Further analysis will be described in the following sections.

3.3. Verification of ASPS approach to recognise the imagination

All delta (Δ) features are applied as ANN inputs for classifying the imaginations to evaluate the feature performance which are obtained via the ASPS approach. Two types of supervised ANN, namely Feed forward neural network (FFNN) and learning vector quantisation (LVQ), are utilised with several ANN architectures, datasets as well as train-test combinations to inspect the variability of the classifier's performances.

We evaluated both ANN performance by average percentage accuracy based on the number of predicted values match with actual values (equation (4)). Each model architecture executed for 100 times to investigate the best and average performance which are summarised into result section.

$$\text{Classification accuracy} = \frac{\text{Number of correct predictions}}{\text{Number of total predictions}} \times 100\% \tag{4}$$

4. Result and discussion

A total of 12 delta features are used from time and frequency domain analysis using the ASPS approach, aiming to recognise imaginations based on bespoke experiments. The delta features are given as inputs for the FFNN and LVQ models to investigate the performance of imaginations recognition.

4.1. Feature extraction and selection using the ASPS approach

The ASPS produced delta features of four statistical functions are applied into time domain and two segments of frequency domain according to Fig. 8. According to brain waves theory, the relax state most likely represents alpha wave. Whereas, various mental tasks go through the presentation of beta and gamma waves [14]. The wave amplitude and frequency of each category contain distinct characteristics. So, the state of the relax mind can obviously be differentiated from the brain state with certain imagination. The features of imagination and relax brain signals are expected to be dissimilar, and the degree of variety can be revealed by analysing delta values towards finding the sensitive features. A precise analysis is performed between features sensitivity with individual sensor for each imagination. The influential characteristics of delta features are depicted in a heatmap (see Fig. 9) with colour representation of sensitivity. The analysis steps are: 1) observing the combination of delta feature values for individual imagination, 2) comparing imaginations with each other, 3) analogising ASMs between two subjects. The first step is to discover

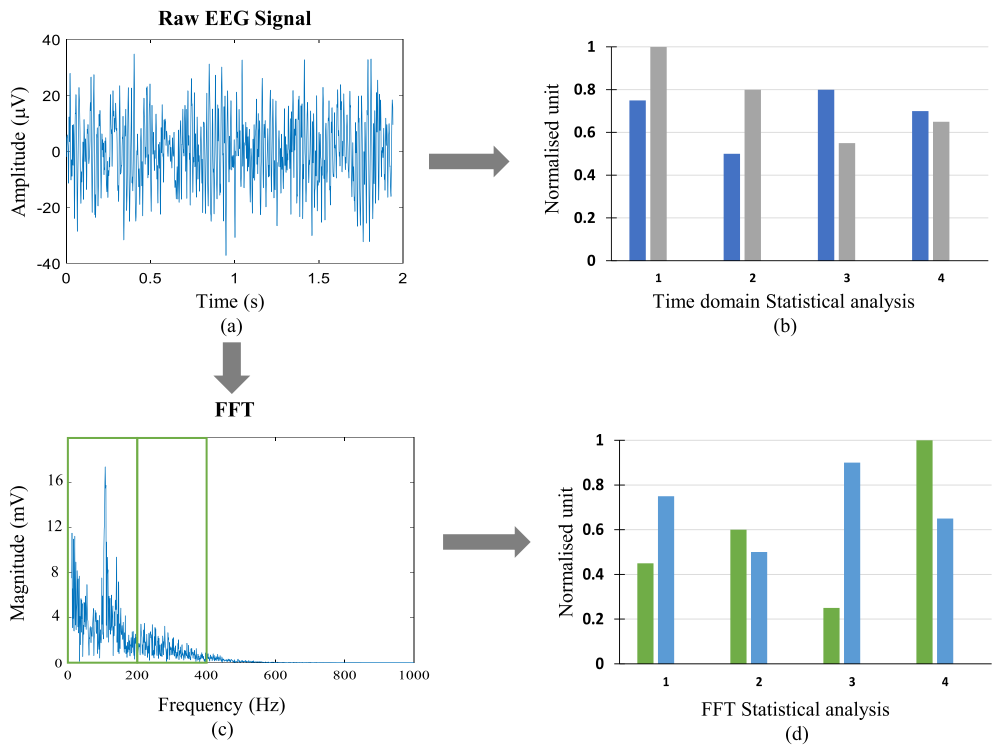


Fig. 8. An example of feature extraction steps.

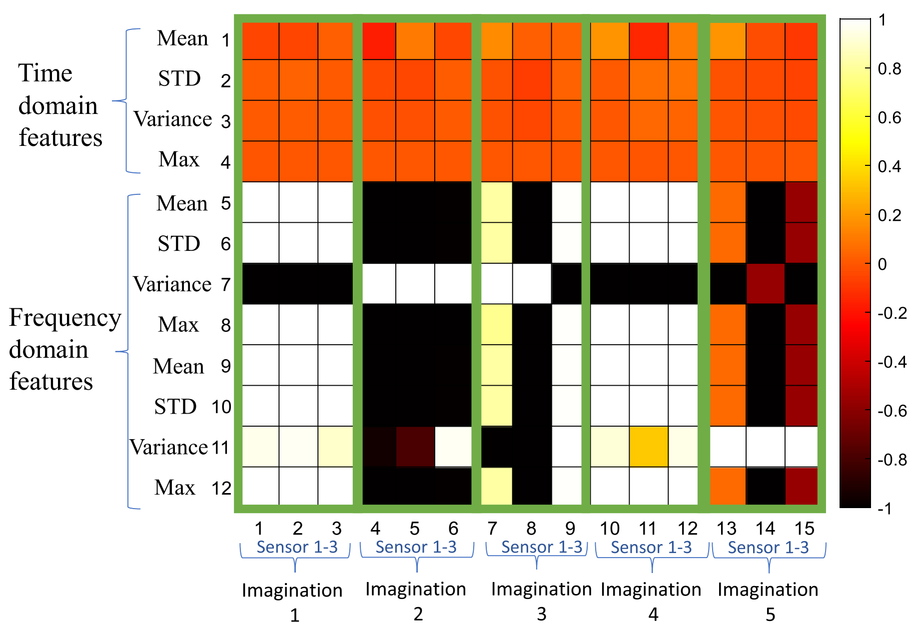


Fig. 9. Heatmap of imaginations with selected features.

the change in feature values and the availability of a unique combination of features within an imagination. From the analysis it is noticeable that, the uniqueness of features combination allows different values between lowest and highest sensitivity. The second analysis step is vital for inspecting the ability of features to differentiate an individual imagination. As seen in Fig. 9, there are two major findings: firstly, the statistical function named variance (SCF 7 and 11) of FFT conveys a significant alteration with rest of the delta features; and secondly, the individual sensor shows the distinctive behaviours for each imagination. A prominent difference between sensors is notable for imagination 3 and 5. Imagination 1 and 4 are distinguished with respect to feature number 11. On the other hand, imagination 2 is contrary compared to imagination 1 and 4. Therefore, they make a unique combination of features for each imagination. Yet, a little resemblance is noticed between imagination 1 & 4; and 3 & 5. Considering them, we prepared two additional separate datasets for verification where the 2nd dataset contains imagination 2, 3, 4 and 5. And the 3rd dataset includes imagination 2, 4 and 5.

Therefore, all 12 delta features are selected since the selection of only high sensitivity features (both positive and negative) is insufficient to recognise an imagination among the five imaginations.

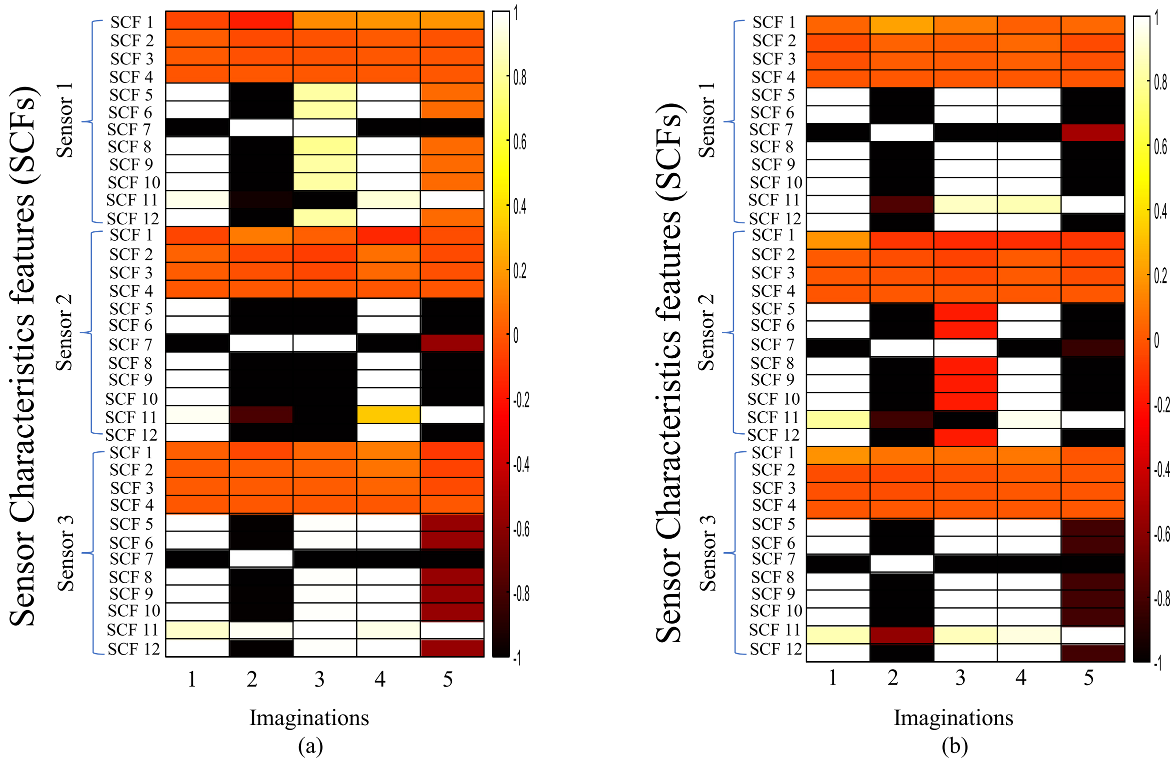


Fig. 10. The Association matrix (ASM) with all imagination for subject 1 (a) and 2 (b).

Also, the likelihood of a comparable pattern for any two/three imaginations becomes higher which in turn reduces the imagination's identity characteristics. Fig. 10 displays the 3rd analysis step which produces the mapping of all five imaginations (Experiment A) between two subjects. In Fig. 10, almost identical patterns of imaginations are shown between the two subjects. Imaginations 1, 2 and 4 have consistent combinations for both subjects. For imagination 3, and sensors number 2 and 3 show close sensitivity patterns. However, sensor 2 differs within ± 0.5 between subjects and it has lower sensitivity than sensor 1 in both cases. For imagination 5 both subjects have identical levels between sensor 2 and 3. For sensor 1 of imagination 3 and 5, SCF number 7 and 11 have opposite combinations between subjects though both SCFs, making a unique combination in either case. Therefore, most of the features are found common which can characterise the imagination 3 and 5.

4.2. Performance of classifiers

The verification part is designed and implemented with few steps according to Fig. 11. ANN is evaluated with three datasets where, 1st, 2nd and 3rd datasets are prepared with the features of 5, 4 and 3 imaginations respectively. The 1st dataset contains all five imaginations, based on the analysis of the 2nd and 3rd datasets. The 2nd dataset includes imagination 2, 3, 4 and 5. The 3rd dataset is consisted of imagination 2, 4 and 5. Different train-test combinations are designed to check the performance of datasets and ANN architectures, see Fig. 11. FFNN is one of the oldest and most widely used ANN. It enables an effective computational model for medical diagnosis where one or more hidden layers are organised to train a model from a set of labelled input data and desired output labels are produced by processing numerous artificial neurons [63]. LVQ is another type of ANN and suitable for multiclass classification. It consists of a competitive layer followed by a linear layer and suitable for multiclass classification [64]. Models are experimented with diverse neuron numbers (1 to 100) for one layer and 4 combinations of neurons for two layers.

The two types of ANN, FFNN and LVQ are used as classifiers to verify the extracted and selected delta features using the ASPS approach. ANN architectures were experimented with using various combinations; firstly, considering the number of hidden layers and number of neurons in each layer; secondly considering different combination of training and test data from two subjects and finally, three different combinations of imagination datasets. Six ANN architectures with different combinations of hidden layers and number of neurons in hidden layers are shown in Table 3. Four different train-test models are considered based on different combinations of training and test data from two subjects. These models are presented in Fig. 11 and each model is executed using six ANN architecture resulting in 24 different combinations of model and ANN architecture. Each of these 24 combinations are run with 5, 4 and 3 imaginations as described in the previous section, respectively. All ANN were executed for 100 times to observe the best and average performances for each case. The best performances for all models are summarised in Fig. 12, where the performance of recognising imagination is plotted based on train-test models.

Fig. 12(a) and (b) present the performances of models for bespoke experiments where both training and testing data belong to the same person. The result for recognising five imaginations varies with subjects; highest performance is achieved 80% using LVQ and FFNN with 1 hidden layer for subject 1, whereas subject 2 attains 100% using the same architecture for five imaginations. Both LVQ and FFNN (1 hidden layer) are very adequate to obtain 100% accuracy in terms of 2nd and 3rd datasets for both models. On the other hand, Fig. 12(c) and (d) present the performance of models which are trained with one person and tested with both persons. In these cases, five and four imaginations are recognised with maximum accuracy using LVQ of 80% and 87.5% respectively. A common perception for all instances is found that any model can recognise 3 imaginations with 100% accuracy. Another finding

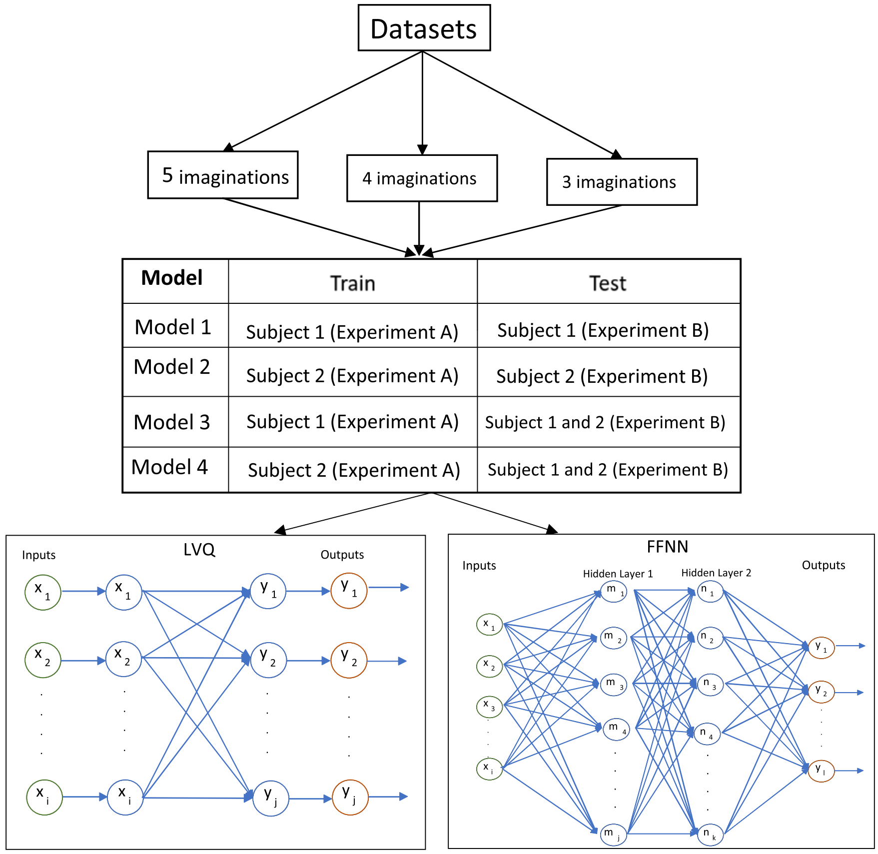


Fig. 11. The design of the verification steps suing neural networks.

Table 3
ANN model architectures for commands classification.

Layer architecture index	ANN type	Number of commands for classification	Number of neurons in layer 1	Number of neurons in layer 2	Number of models run
1	LVQ	5, 4, 3	$N, N = 1, 2, \ldots 100$	N/A	100
2	FFNN	5, 4, 3	$N, N = 1, 2, \ldots 100$	N/A	100
3	FFNN	5, 4, 3	36	36	100
4	FFNN	5, 4, 3	36	72	100
5	FFNN	5, 4, 3	72	36	100
6	FFNN	5, 4, 3	72	72	100

is that FFNN with two hidden layers mostly attain lower performances (5 imaginations =< 80%, 4 imaginations =< 75%) which indicates that the ANN architectures with one hidden layer are well equipped for ASPS approach verification in terms of this EEG signals experiment.

Considering all models with 100 runs, an average ANN performance for 5, 4 and 3 imagination recognition are plotted in Fig. 13. The box and whisker plot clearly shows that 3-imaginations has average accuracy between 72–100%. 4-imaginations and 5-imaginations attain an average accuracy of up to 77% and 67.40% respectively. An investigation for the average performance deviation between four train-test models is illustrated with Fig. 14. The outputs are influenced by the quality of imagination made by the subject. For example, the overall achievement shows better with all imaginations while the ANN are trained by subject 2. Similar agreement is investigated between different models and dataset performances, suggesting further that the ASPS approach has the capability to extract the necessary brain signal features towards BCI developments.

According to similar classifiers' performance in brain signal processing, some research studies demonstrate divergent ranges of performance. For example, [30] achieved 31–86% accuracy for five mental tasks classification using LVQ. With similar experiment using Back propagation neural networks and SVM [51] attained 64–84% accuracy. The performance mainly fluctuates for the extent of experiment, datasets, and classifiers. In this research, overall best performance of our bespoke experiments achieved accuracy of 80–100% for recognising five imaginations using both FFNN and LVQ classifiers.

5. Conclusion and future work

Patients with Completely Locked-in-Syndrome (CLIS) due to accidents, brain damage, MND (ALS) do not have a method of communication with the outside world other than thoughts. Brain computer interface (BCI) can be used to address this problem, where brain signals can be converted into control and screen commands. Numerous techniques with both traditional and novel methods have been tested in regard to brain signal processing, nevertheless research in this area, as always, is demanding towards the development of a more effective system. This paper addresses

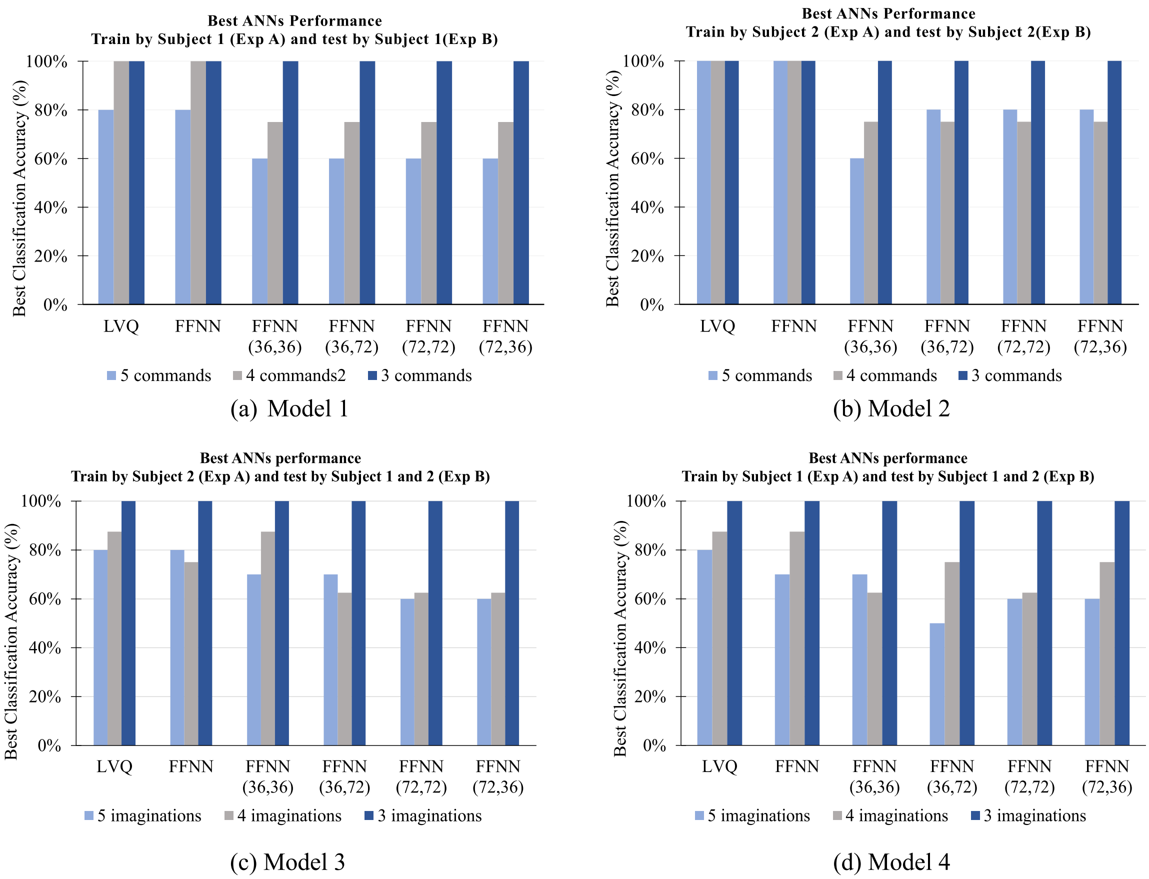


Fig. 12. Best classification accuracy of four models for all ANN architecture.

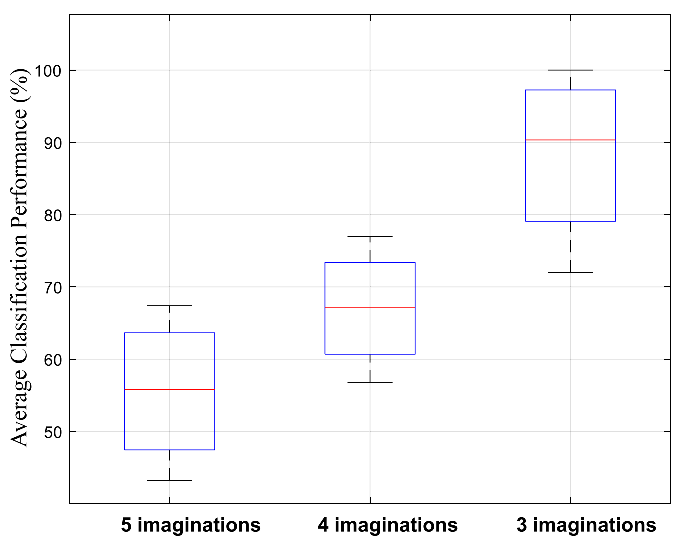


Fig. 13. The average performance of 3 datasets for all models.

this issue by presenting a novel method towards a low-cost and affordable BCI system via using of thoughts and imaginations.

This paper has proved that the ASPS approach, which had been used in other applications before, is a powerful feature extraction method for recognising various imaginations. The difference between previous studies and this research is that a certain combination of high-low sensitive features can be extracted through ASPS approach which are able to classify the imagination. Previous studies used only highly sensitive features to detect machinery fault. To reduce the cost of a future system based on our method, this paper uses 3 sensors and limited number of features. This proposed method is designed and tested for individual subject as bespoke experiment and later two subjects are tested from training by one of the subjects' data to observe the capability of the method at this stage. It will motivate the study to be generalised to broader population. Sensitive features are obtained through time-domain and frequency domain (FFT) analysis using the ASPS approach as it allows multiple signal processing techniques to be integrated, reducing any extra experimental work, time, and cost. The verification by two different types of ANN (LVQ and FFNN) for the proposed method attained accuracy between 80 and 100% to recognise five imaginations. For four imaginations this research has achieved success rate between 87.5 and 100%. A 100% accuracy has been obtained when recognising 3 imaginations. Hence, this system should enable three types of commands of a keyboard to allow communication (e.g. arrow up, arrow low and select). This work shows that recording EEG signals with a combination of relax and mental tasks will allow the extraction of sensitive delta features and using the ASPS approach, sensitive and unique features can be efficiently identified with uniqueness that will enormously influence BCI systems for classifying brain signals. This would allow complex communication of feelings and needs via thoughts.

The paper aimed to explain the methodology in detail using a simplified example to presents the capability of the ASPS approach for BCI. Future work will present the results of relatively high number of volunteers, sensors and signal processing methods to statistically quantify the benefits and best location of sensors.

Human and animal rights

The authors declare that the work described has been carried out in accordance with the Declaration of Helsinki of the World

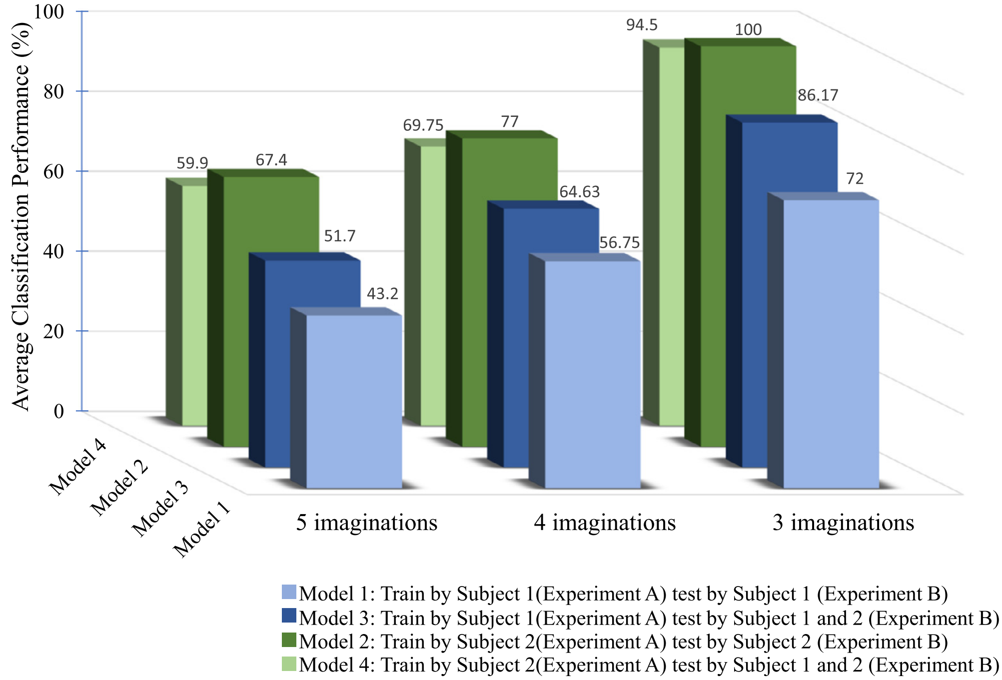


Fig. 14. The average performance comparison for subject-wise training and imaginations.

Medical Association revised in 2013 for experiments involving humans as well as in accordance with the EU Directive 2010/63/EU for animal experiments.

Informed consent and patient details

The authors declare that this report does not contain any personal information that could lead to the identification of the patient(s) and/or volunteers.

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Author contributions

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.

Declaration of competing interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

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