AUTOMATION OF PRE-PROCESSING AND FEATURE EXTRACTION PARAMETER SELECTION FOR A SINGLE-TRIAL P300-BASED BRAIN-COMPUTER INTERFACE USING A GENETIC ALGORITHM

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ABSTRACT

The P300 evoked potential is commonly used in the Brain-Computer Interface (BCI) paradigm to translate the intentions of a user into commands for external devices. Identifying the P300 response in the recorded brain activity is facilitated using machine learning. Feature extraction is performed on the collected data in order to reduce its dimensionality. Dimensionality reduction is necessary in order to avert the Hughes effect associated with high-dimensional training data whereby an exponentially greater number of training examples are required to maintain classifier generalisation as feature dimensionality increases. In general, the classification stage of a BCI is the only avenue through which the BCI is tuned to the user's unique brain activity. Subject-specific BCI tuning is necessary in order to cater to the inherent inter-subject physiological differences that manifest itself in the EEG. Additionally, owing to inter-subject physiological dissimilar, each user would also possess an optimal pre-processing and feature extraction scheme. However, the pre-processing and feature extraction stages of a Brain-Computer Interface which precede classification are usually fixed and insensitive to the user.

In this work, two-stage genetic-optimisation is utilised to tune a BCI to a user at the levels of pre-processing and feature extraction thereby completely removing the need for subjective human expertise in the parameter selection process. In the first stage of genetic-optimisation, a Genetic algorithm is used to select the EEG channels from which single-trial P300 features are obtained. The second stage of genetic-optimisation involves the determination of the high cut-off frequency of a digital filter used to pre-process each EEG channel and the down-sampling factor used to produce temporal features per channel.

Using all 32 EEG channels and the default feature extraction and pre-processing parameters proposed in [11], the average single-trial P300 classification error across 8 subjects was 42.10%. The classification error was reduced to 37.83% using the two-stage genetic-optimisation method proposed in this paper. One disabled subject's classification error decreased by 10.79%. The results suggest that classification error can be reduced and that it may be feasible to automate the process of BCI parameter selection using a genetic algorithm approach. Additionally, the reduction in the EEG channel count from 32 to 18 as proposed by the GA results in a shorter subject preparation time and a reduction in the computational and memory requirements of BCI operation as well as the quantity of consumables necessary to perform data collection.

Keywords: BCI, P300, Genetic Algorithm, Optimisation, Automation

1 INTRODUCTION

A Brain-Computer Interface (BCI) is a system that permits users to control external devices using only their brain activity [1]. In the BCI paradigm, users are instructed to perform a mental or physical task that signifies their intended command. For example, a BCI user may focus on a directional arrow presented on a computer screen in order to change the travel direction of an autonomous vehicle. The performance of representative mental and physical tasks in the BCI paradigm results in the identifiable modulation of a user's brain activity features. The BCI, through a recording modality such as electroencephalography (EEG), identifies brain feature modulation and uses it to classify the user's command.

Common BCI application platforms are cursor control [2], spelling systems [3] and wheelchair navigation [4]-[5]. These applications highlight the practical utility of BCI technology for the disabled community since they allow environmental interaction and communication without the need for pre-existing neuromuscular capabilities. The features of brain activity commonly used for brain-computer interfacing are visually evoked potentials (VEP) [6]-[7], sensorimotor rhythms [8]-[9] and slow cortical potentials (SCP) [10]. VEPs can be classified into either the Steady State Visually Evoked Potential (SSVEP) or the P300 VEP. The SSVEP is manifested as a spike in the EEG's power spectrum at the flashing frequency of a stimulus to which the user is observing. The P300 appears as an electropositive peak in the EEG around 300-600ms following the observation of a rare, target or deviant stimulus. In general, the P300 occurs in the 0-8Hz portion of the frequency spectrum.

For the purposes of Brain-Computer Interfacing, the P300 response is evoked using an oddball paradigm. The oddball paradigm is a stimulus presentation scheme in which a target stimulus is delivered amongst more frequently occurring non-target stimuli. In a P300-based BCI, the target stimulus is the stimulus which represents the user's command. The other stimuli, which represent other possible commands, are considered to be non-target. Therefore, the EEG segment following the presentation of the stimulus which encodes the user's command contains the P300. Consequently, the user's command can be identified through the inspection of post-stimulus EEG segments for the P300 response.

Identifying the user's command from the collected EEG is achieved using pattern classification. In general, BCI users participate in data collection sessions which produce labelled training examples for a machine learning classifier. Subsequent to classifier training, the BCI can be used in the online setting with the trained classifier. The classifier stage represents the aspect of the BCI which is tuned to the user. This is necessary as, owing to inter-subject physiological dissimilarity, universal classifiers would not be optimal for every subject.

The feature extraction and pre-processing stages are generally fixed and are insensitive to the user [11]-[13]. However, owing to inter-subject physiological dissimilarities, there would be an optimal feature extraction and pre-processing option for each subject. However, obtaining the optimal feature extraction and pre-processing scheme for a P300-based BCI manifests itself as a discontinuous optimisation problem. Owing to its mathematically intractable nature, the traditional analytical methods of gradient descent/ascent are rendered inappropriate.
Genetic Algorithms (GA) however are ideally suited for this sort of problem. GAs are

random search optimization techniques based on the mechanics of natural selection. GAs employ genomic trading, gene mutation and elitism in order to increase the possibility of finding the optimal solution. It is important to recognise that unlike methods such as Artificial Neural Networks (ANN), a GA makes no assumption about the underlying model of the process under optimisation. As such it is a strictly "black-box" approach. The GA alters the inputs to a user-defined fitness function in order to improve the current solution without regard to the process's underlying model or the solution gradient. This is particularly useful for mathematically intractable problems such as the one of optimising feature extraction and pre-processing parameter selection. GAs are generally employed when an exhaustive search would require an impractical amount of time using the available computational allowance.

In this work, two-stage genetic-optimisation is used to obtain feature extraction and pre-processing parameters for a P300-based BCI operating with a Bayesian Linear Discriminant Analysis (BLDA) classifier. The first stage of genetic-optimisation decides the EEG channels from which to extract spatiotemporal P300 features. The second stage of genetic-optimisation attains the high cut-off frequency of a digital filter and the down-sampling factor used to extract temporal features per EEG channel.

2 MATERIALS AND METHODS

2.1 Dataset Description: Experimental Paradigm and Recording Circumstances

Five subjects with varying levels of disability and four able-bodied subjects were presented with a display of six images of household items on a laptop screen as shown in Figure 1 and were instructed on focus on a pre-designated target image [11]. The six stimuli were highlighted in a random sequence by changing the overall brightness of each image sequentially. Each image was highlighted for 100ms followed by a 300ms blank period in which no image was highlighted. This blank period is referred to as the Inter-Stimulus Interval (ISI). The presentation of six stimuli is referred to as a trial. A collection of trials in which the target image is constant is termed a run. There were at least 20 trials per run for all subjects. A collection of six runs in which each run contains a different target image is referred to as a session. Each subject completed four sessions within a time period of less than two weeks. The hierarchical data set structure is embodied by Figure 1.

Concurrent with the stimuli presentation, EEG was recorded at a frequency of 2048Hz at 32 sites according to the extended 10/20 International Electrode Placement System. Subject 5's dataset was discarded due to his inability to receive user instruction on how to use the paradigm.

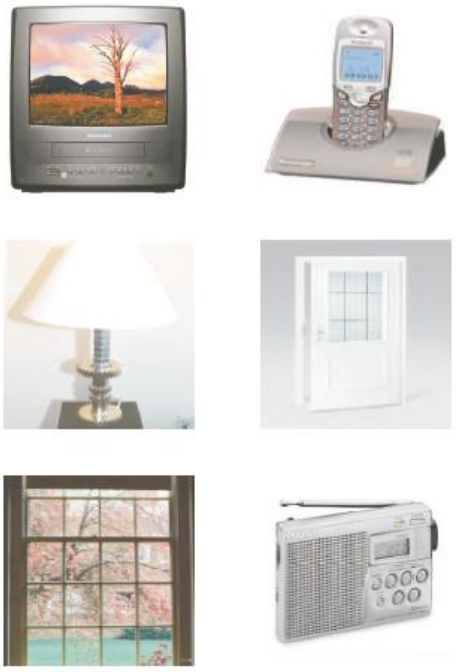

Figure 1: Display of Stimulus Presentation Paradigm [11]

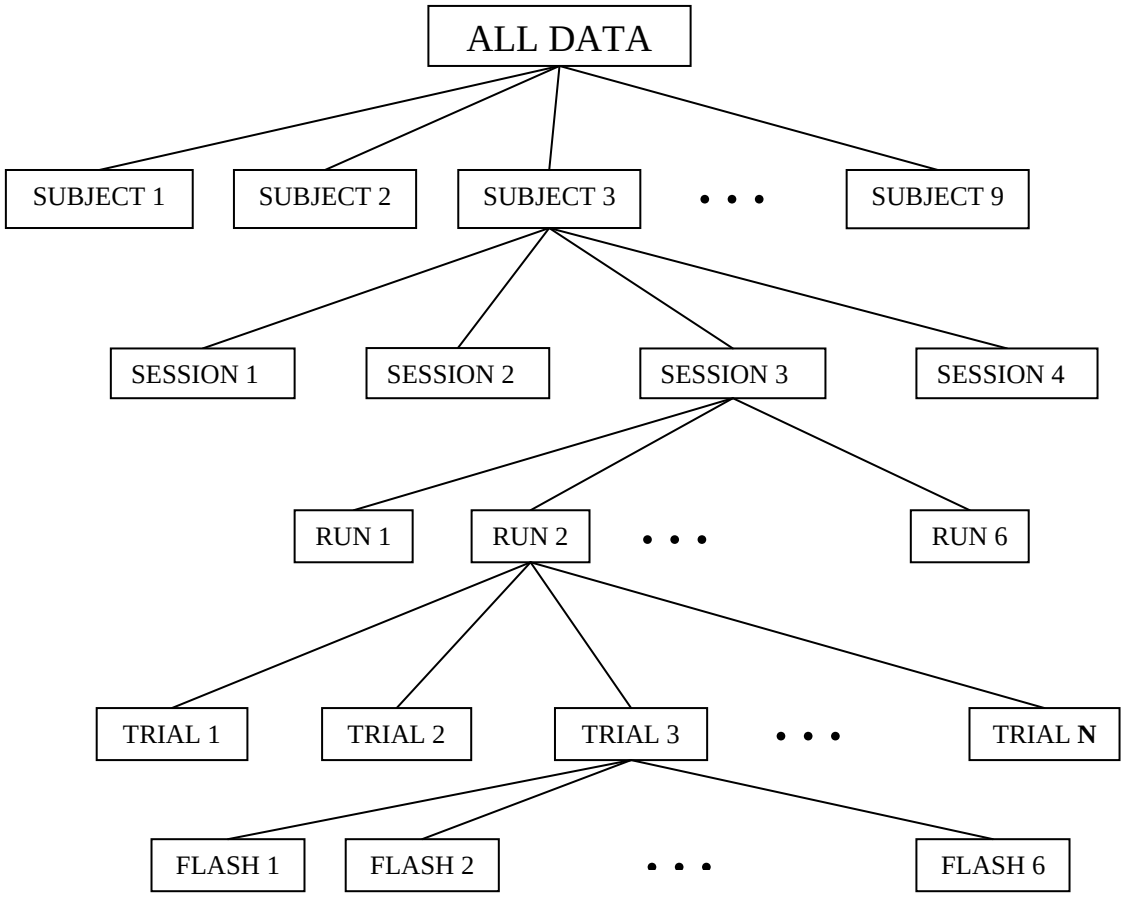

Figure 2: Hierarchical structure of dataset

3 GENETIC ALGORITHM

GA is a random search optimisation technique based on the mechanics of natural selection [14]-[15]. A GA is initialised by creating a random set of solutions to the optimisation problem known as individuals. The individuals are said to form a population. Each individual is evaluated to determine their fitness at solving the problem at hand. In a GA, this is done by means of a fitness function which quantifies the individual's fitness.

At the conclusion of each GA iteration, the constitutive numerical elements of most of the individuals known as genomes are altered in an attempt to better their overall fitness. The very best solutions are retained and are allowed to propagate to the next iteration unaltered. This is referred to as elitism and it ensures that the superior individuals are retained in the population. The least fit individuals are mutated whereby their genomes are altered by the addition of a random variable. The individuals of intermediate fitness are combined at the genomic level in a process termed crossover. Both crossover and mutation ensures genetic diversity and allows the algorithm to search a larger space thus increasing its chance of locating the problem's global optimum. This process is iterative and runs for a specified number of times before a pre-defined stopping criterion is met.

4 TWO-STAGE GENETIC-OPTIMISATION

4.1 Stage 1: Genetically-optimised channel subset selection

As aforementioned, there are four sessions of EEG data per subject. For each subject, single-trial session 1 features were used to train the BLDA classifier and single-trial session 2 features were used to test the classifier. Session 2 was used as the testing set as opposed to session 1 to provide an independent measure of classifier generalisation. The GA manipulated the channels from which features were extracted in order to reduce this classification error. The GA-based channel proposal was therefore based only on sessions 1 and 2. In order to independently test this channel proposal, single-trial session 3 features were used to train the BLDA classifier and single-trial session 4 features were used to test the classifier. In addition to using the GA proposed channel subset, the standard channel subsets from [11] were used for the sake of comparison.

4.2 Stage 2: Genetically-optimised frequency filtering and feature extraction

The second stage of genetic optimisation involved the selection of feature extraction and pre-processing BCI parameters. In [11], each EEG channel was forward-reverse filtered using a 3rd order band-pass Butterworth digital filter with 3dB cut-off frequencies at 1Hz and 12Hz. The 1-second EEG segments following stimulus presentation were then extracted and down-sampled by a factor of 64 to produce a set of temporal features per channel. The temporal feature vectors of each channel were then combined to produce a spatiotemporal feature vector pertaining to stimulus intensifications.

As before, single-trial session 1 features were used to train the BLDA classifier and single-trial session 2 features were used to test the classifier's accuracy. The GA minimised the classification error by altering the high cut-off frequency of the Butterworth filter and the down-sampling factor used for feature extraction. The channels from which temporal features were extracted were based on the output of the first GA. Following the execution of the second GA, the feature extraction and pre-processing parameter proposals were independently tested using sessions 3 and 4 as training and testing sets respectively.

5 GENETIC ALGORITHM SETUP PARAMETERS

Two-stage genetic optimisation was implemented in MATLAB 7.8.0.347 using the Genetic Algorithm Optimisation Tool. The setup parameters for both GA optimisation problems are given in Table 1 and Table 2.

Table 1: GA setup parameters for 1st stage of genetic-optimisation

GA Parameter	Value
Population coding	Binary string
Population size	50
Individuals per Population	32
Fitness value	BLDA classification error using single-trial session 1 features to train and single-trial session 2 features to test
Elite count	50 (0.1 fraction/proportion)
Crossover fraction	0.8
Crossover function	Scattered
Mutation fraction	0.1
Migration parameters	Fraction=0.2, Interval=20
Stopping Criteria	Maximum number of generations=100 Minimum fitness value=0

Table 2: GA setup parameters for 2nd stage of genetic-optimisation

GA Parameter	Value
Population coding	Double vector
Population size	50
Individuals per Population	2
Fitness value	BLDA Classification error using single-trial session 1 features to train and single-trial session 2 features to test
Elite count	50 (0.1 fraction/proportion)
Crossover fraction	0.6
Crossover function	Scattered
Mutation fraction	0.3
Migration parameters	Fraction=0.2, Interval=20
Stopping Criteria	Maximum number of generations=100 Minimum fitness value=0

6 RESULTS

The EEG channels selected by the first-stage GAs are highlighted in Figure 3 for subjects 1-4 and subjects 6-9. The data for subject 5 contained significant noise and was not provided for this study.

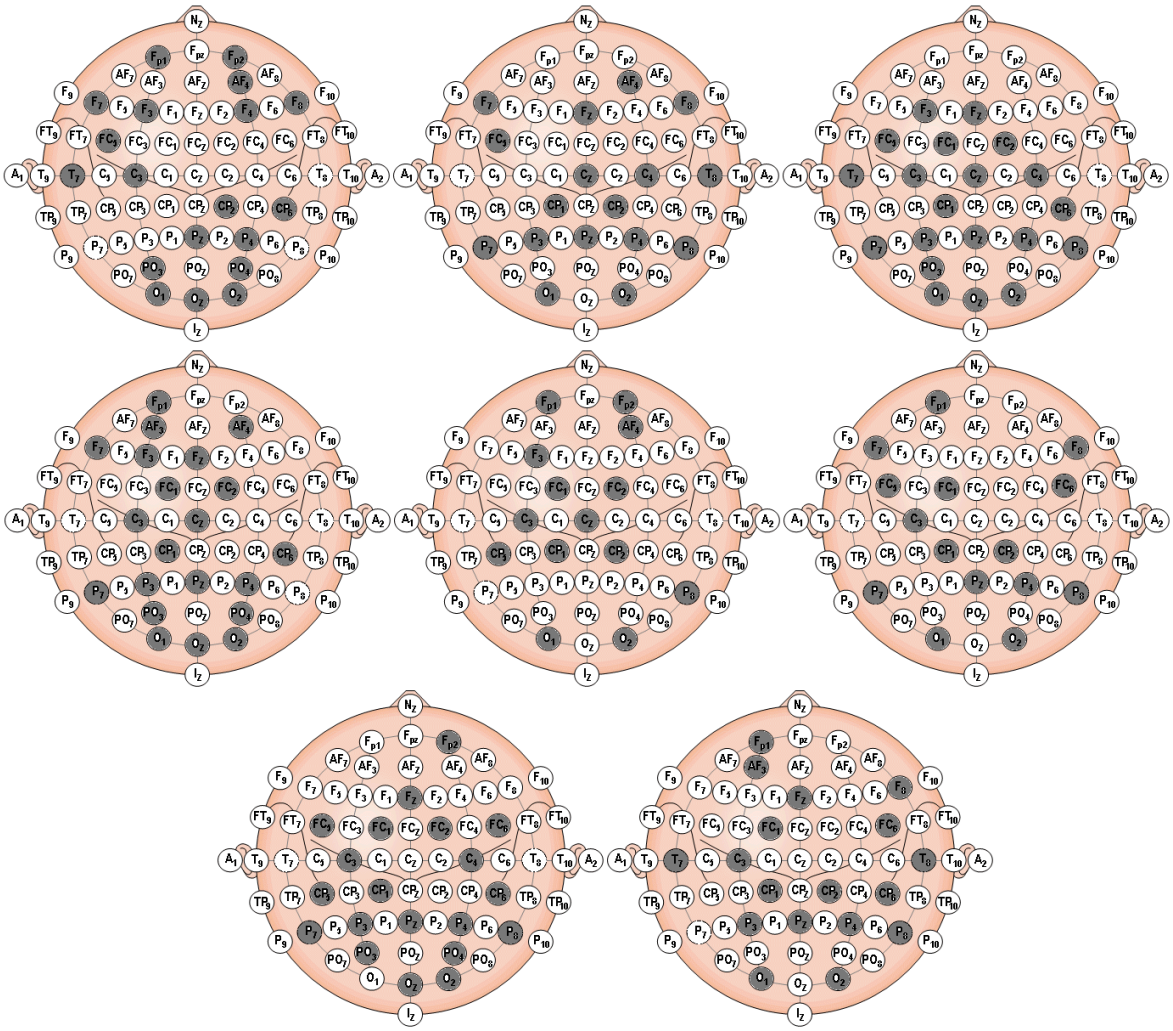

Figure 3: EEG Channels Chosen by 1st stage of genetic-optimisation (the top row of images corresponds to subjects 1-3; the second row corresponds to subject 4, 6 and 7; the bottom row corresponds to subjects 8 and 9)

The total number of times each channel is selected by the first stage of genetic-optimisation summed across for all eight subjects are given in Figure 4.

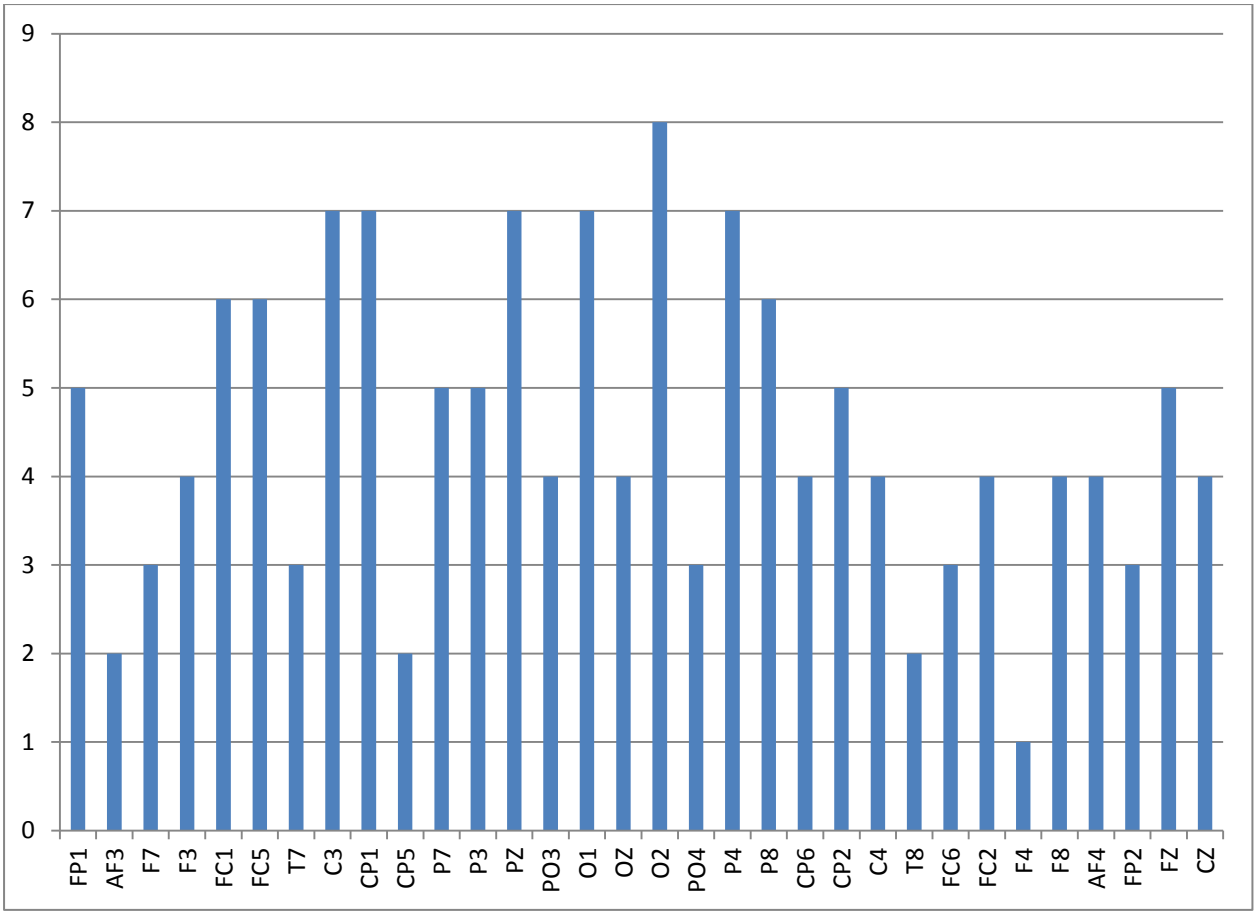

Figure 4: Frequency of selected EEG channels across eight subjects for the first stage of genetic-optimisation

The pre-processing and feature extraction parameter proposals made by the 2nd stage of genetic-optimisation are given in

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Table 3: Genetic-optimisation proposals for high cut-off frequency for a 3rd order forward-reverse band-pass Butterworth filter applied to each channel and down-sampling factor used to create temporal features per channel

Subject	Low cut-off frequency (fixed and unaltered by GA)	High cut-off frequency	Down-sampling factor
1	1Hz	8.4942Hz	76
2	1Hz	8.1563Hz	72
3	1Hz	10.1596Hz	39
4	1Hz	8.6068Hz	74
6	1Hz	11.2673Hz	46
7	1Hz	8.7444Hz	70
8	1Hz	9.6848Hz	37
9	1Hz	11.0756Hz	46

The percentage classification errors attained by a BLDA classifier trained on single-trial session 3 features and tested on single-trial session 4 features using the output of 2 stages of genetic-optimisation are given in Table 4.

Table 4: Single-trial classification error for 8 subjects for a BLDA classifier trained on single-trial P300 features from session 3 and tested on single-trial P300 features from session 4 (lowest misclassification errors for each subject is emboldened)

Subject	4-channels	8-channels	16-channels	32-channels	Genetic-Optimisation		
					Stage 1	Number of channels	Stage 2
1	71.53%	64.96%	67.15%	59.12%	59.12%	19	**57.66%**
2	65.03%	62.94%	60.84%	61.54%	60.84%	17	**55.24%**
3	27.94%	25.74%	**22.06%**	24.26%	23.53%	20	**22.06%**
4	56.12%	43.88%	39.57%	38.85%	33.81%	21	**28.06%**
6	39.13%	27.54%	28.99%	26.09%	25.36%	14	**18.84%**
7	44.06%	44.76%	34.27%	32.87%	**30.77%**	15	38.46%
8	43.70%	24.44%	27.41%	28.15%	27.41%	20	**20.74%**
9	67.39%	63.04%	**61.59%**	65.94%	63.04%	18	**61.59%**
AVERAGE	51.86%	44.66%	42.74%	42.10%	40.49%	18	**37.83%**

7 DISCUSSION

In general, the classifier stage of a BCI represents the only avenue through which the BCI is tuned to the user. On the presentation of labelled training examples, the classifier's free parameters are adjusted so as to minimise its misclassification error on a testing set or some other independent measure of classifier performance. Subject-specific BCI tuning is necessary in Brain-Computer Interfacing because of the intrinsic physiological dissimilarities that exist between subjects. However, the feature extraction and pre-processing stages of a BCI are generally fixed and insensitive to the user. In this work, the parameters of the pre-processing and feature extraction stages of a BCI were tuned to eight subjects using two stages of genetic optimisation. This was done to automate the parameter selection process, usually performed by a human expert, associated with BCI development and evaluate the performance of the automated parameter selection.

The first stage of genetic-optimisation entailed the selection of EEG channels from which single-trial features were extracted. At the conclusion of the first stage, the GA channel proposals were compared to the four standard EEG channel subsets in [11]. Using the standard channel subsets, a trend was observed whereby increasing the number of channels decreased classification error. This trend was not followed using the GA-based channel proposal. The channel count of the GA-based channel proposal was reduced by approximately half (from 32 to 18) whilst offering increased classification accuracy. Compared to the standard 16-channel subset of [11], the classification error fell from 42.74% to 40.49%. This indicates that the GA rejected the noisy EEG channels whose features degrade classification. The reduced channel count is advantageous in the context of an online programme of experimentation as this translates to less time for subject preparation and a commensurate decrease in the amount of consumables needed to perform data collection. Additionally, the computational time needed for feature extraction, pre-processing and classification is also shortened.

The second stage of genetic optimisation involved the selection of the high cut-off frequency of a 3rd order forward-reverse Butterworth digital filter and the down-sampling factor used to produce temporal features for each EEG channel. Subsequent to the second stage of genetic-optimisation, the average classification error dropped further to 37.83% at no significant increase in computational requirements. Furthermore, as shown in Figure 3 and
, each subject has a different optimal EEG channel subset as well as frequency cut-off and down-sampling factor. This indicates it is feasible to tune the pre-processing and feature extraction stages to a BCI user.

The total channel frequencies as obtained by the first stage of genetic optimisation across 8 subjects indicate the relevant importance of the EEG channels in the context of P300-based BCIs. It can be seen from Figure 4 that EEG channel O2 was chosen for every subject which indicates it is a very important channel regardless of subject and cap placement parameters. Additionally, channels PZ, CZ, OZ and FZ all have selection scores of at least 4 which indicate that they are also important channels. This is compatible with the predominant knowledge in the field. In contrast, channel F4 was only chosen once which indicates that it is much less important in the context of EEG-based P300-driven BCIs.

Additionally, the genetic-optimisation resulted in improved classification performance for disabled subjects (1-4) as well as able-bodied subjects (6-9). The proposed method is therefore unbiased to a user's pre-existing level of physical ability.

8 CONCLUSION

Two-stage genetic-optimisation was used to automate parameter selection in the stages of channel selection, feature extraction and pre-processing for a single-trial P300-based BCI. The average single-trial classification error over 8 subjects was reduced by 4.27% compared to using all available 32 channels and the default pre-processing and feature extraction parameters proposed in [11]. The automation of parameter selection for the feature extraction and pre-processing stages through genetic-optimisation completely removes the need for subjective human expertise in the BCI development process in addition to yielding better classification performance on average. It was found that each subject possessed a unique set of optimal BCI design parameters which indicates it is feasible to tune a BCI's design parameters to its users.

9 RECOMMENDATIONS

The results indicate that BCI tuning at the stages of pre-processing and feature extraction is possible using GAs. A possibility for future work involves the investigation of analytical methods for feature extraction and pre-processing parameter selection since this will reduce the computational requirements of parameter searching and allow the approach to be used in the online setting that is, immediately following training data collection and preceding classifier implementation.

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