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IMAGE & SIGNAL PROCESSING

EEG electrode selection for person identification thru a genetic-algorithm method

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Abstract
New biometric identification techniques are continually being developed to meet various applications. Electroencephalography (EEG) signals may provide a reasonable option for this type of identification due its unique features that overcome the lacks of other common methods. Currently, however, the processing load for such signals requires considerable time and labor. New methods and algorithms have attempted to reduce EEG processing time, including a reduction of the number of electrodes and segmenting the EEG data into its typical frequency bands. This work complements other efforts by proposing a genetic algorithm to reduce the number of necessary electrodes for measurements by EEG devices. Using a public EEG dataset of 109 subjects who underwent relaxation with eye-open and eye-closed stimuli, we aimed to determine the minimum set of electrodes required for optimum identification accuracy in each EEG sub-band of both stimuli. The results were encouraging and it was possible to accurately identify a subject using about 10 out of 64 electrodes. Moreover, higher frequency bands required a fewer number of electrodes for identification compared with lower frequency bands.

Keywords Biometric identification · Electrodes selection · Electroencephalography (EEG) · Frequency bands · Genetic Algorithm (GA)

Introduction

There have been significant research efforts in the field of feature extraction from signals, such as thru electroencephalography (EEG) signals. Most feature extraction techniques attempt to exclude a few, if not most, of the electrodes [1]. A reduction in the number of EEG electrodes can reduce processing time (sometimes real-time processing), and reduce algorithmic computational loads to only the active channels corresponding to selected stimuli. Reducing the number of electrodes is also an efficient artifact removal technique [1]. Having fewer electrodes is more convenient for users, lowers power consumption, reduces operation time for the device, and reduces overfitting effects due to the utilization of a large number of redundant channels. As an example, studies that use motor movement as a stimulus try to select electrodes placed over the central region of the brain. This is done because the motor cortex is more active than other parts of the brain during motor/motor imaginary activities [2]. However, the selection of these electrodes is usually left to the discretion of researchers. As such, different studies utilize different sets of electrodes to capture the signals of the very same region of the brain, as summarized in Fig. 1.

The aim of present study is to investigate methods to reduce the number of electrodes that are required to identify subjects with maximum accuracy. If EEG device electrodes are represented as an array of finite cells, then an algorithm is needed that determines which cells to select or not select. This work applied an electrode selection method based on a genetic algorithm (GA).

The main contribution of presented work is to provide useful information about the active electrodes corresponding to each frequency sub-band of EEG signal, and hence to reduce the processing time and data-acquiring cost of future works that use this information. As well as suggesting a new feature

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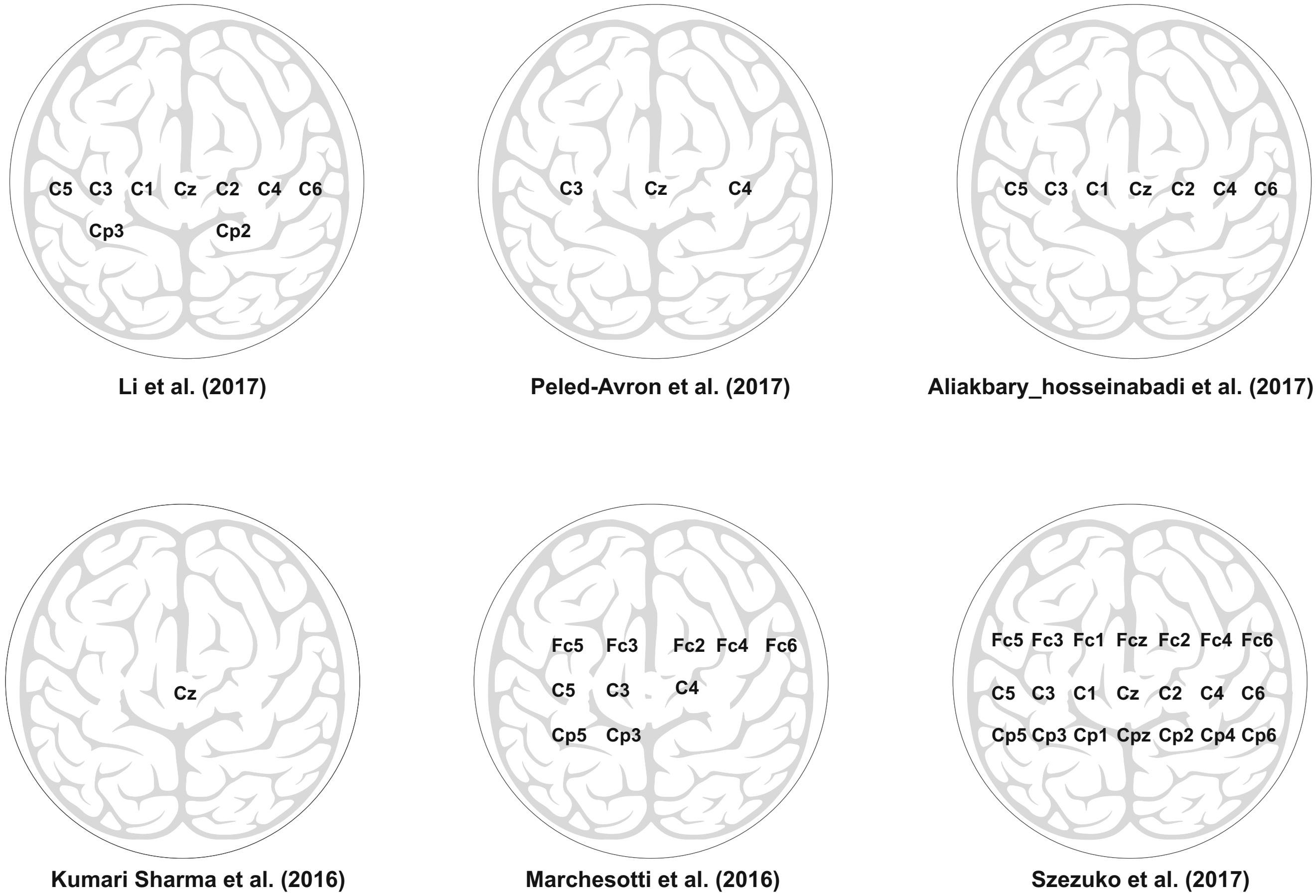


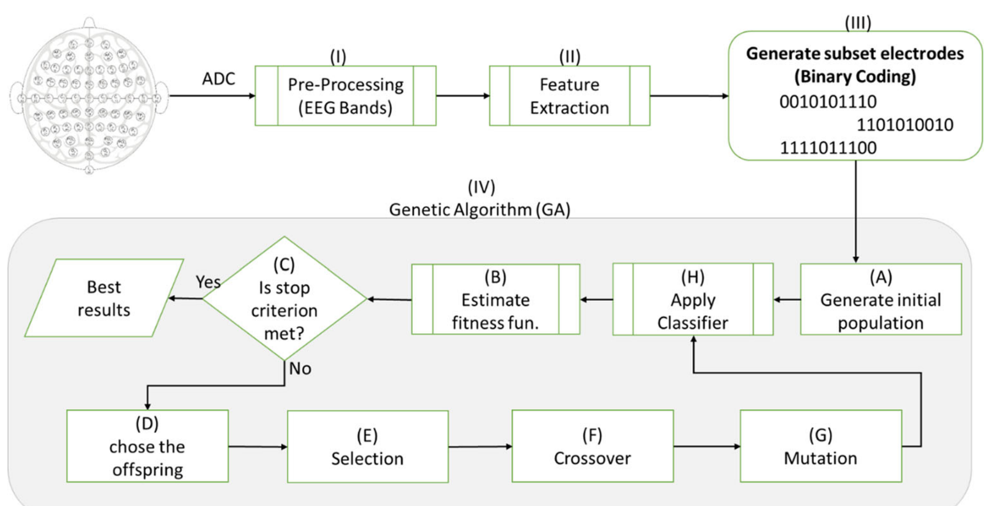
Fig. 1 Selected electrodes for *motor imaginary* stimulus in studies [2–7]

enhancing method that maximizes the total classification accuracy of the system, and also to help in solving the diversity of electrodes' activity problem that exist among individuals.

Additionally, this work complements similar efforts regarding the expansion of the sample space. Most related studies used a sample space of about 15 subjects, whereas the current study included 109 subjects. Further, new enhanced features based on activity ratio were applied. Plus, different kinds of stimuli also tested to determine the optimal set of electrodes corresponding to each sub-band of EEG signal.

There are numerous studies that have proposed algorithms to reduce the number of electrodes or determine the optimal set of electrodes corresponding to particular stimuli. In [8] a sparse common spatial pattern (SCSP) algorithm was used for EEG channel selection. The algorithm selects the least number of channels while maintaining

Fig. 2 The stages of the proposed electrode selection system



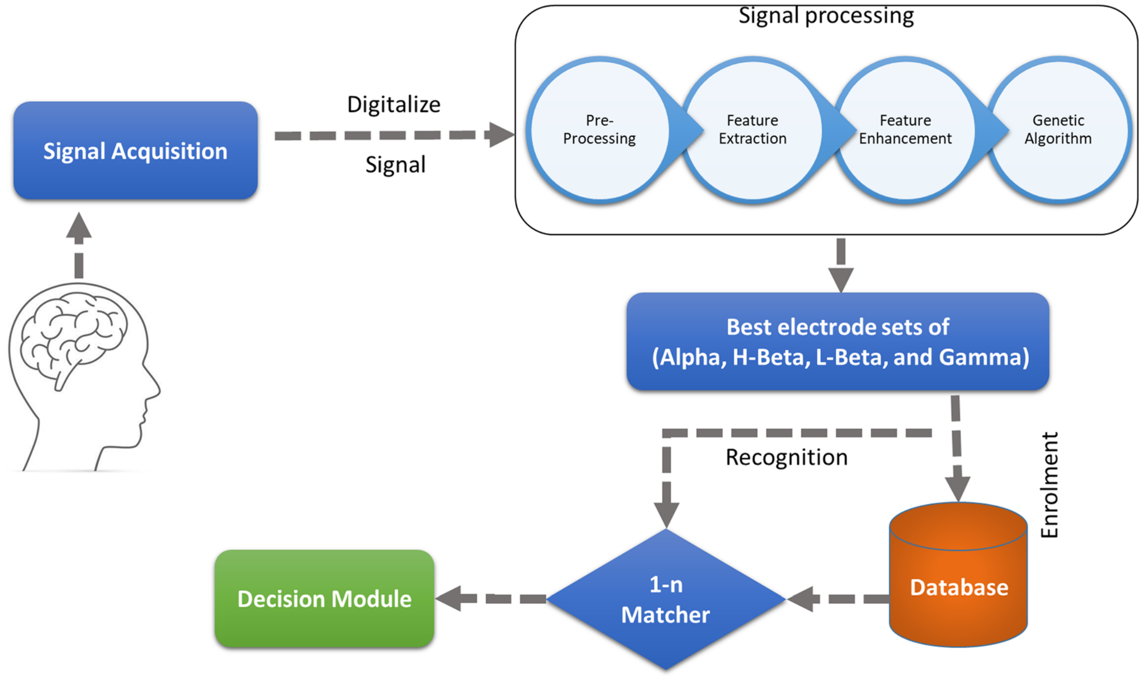


Fig. 3 Block diagram of presented EEG-based identification system

classification accuracy. This algorithm is also used by [9] to optimize EEG signal channels under a constraint imposed on the ratio of variances of EEG signals in different classes and reduced the number of selected channels while preserving classification accuracy. The effects of the number of electrodes, grouping of electrodes and frequency bands were investigate for emotion classification by [10], which also found that using more electrode channels did not guarantee better accuracy. In [11], the performance of PSD features of the Gamma band in biometric authentication was compared to the Delta, Theta, Alpha and Beta bands of EEG signals during an at-rest state, finding that 19 channels provided less EER than the use of a whole set of 64 channels.

Artificial intelligence (AI) techniqeus like GAs are also used for feature and/or electrode selection [12]. In [13], GA was applied for channel selection using the DS of three subjects, and a combination of the number of electrodes and accuracy were utilized to direct the fitness function of the GA. The same combination was used in [14] to investigate the optimal tradeoff between the classification accuracy of a BCI system and the number of selected channels. This tradeoff is essential because different BCI applications have different priorities, with some implementations preferring a minimum number of channels while others favor higher classification accuracy. This study complements previous work and adopts the findings of some published works, such as by using the EEG signal of the same DS [15] for identification purposes, in order to provide better classification accuracy while using a minimum number of electrodes. The results also provide the optimal set of electrodes that result in higher accuracy corresponding to each particular stimuli and the subbands investigated by previous studies.

Table 1 Feature extraction method and its mathematical representation

Feature Name	Mathematical Representation
Mean	$\frac{1}{N}\sum_{i=1}^{N} Ai * Z\text{Я}_{(\mathrm{I})}$ (1)
Standard Deviation	$\sqrt{\frac{1}{N}\sum_{i=1}^{N} \lvert Ai-\mu\rvert^2} * Z\text{Я}_{(\mathrm{I})}$ (2)
Power	$\sum_{i=1}^{N} \lvert Ai\rvert^2/N * Z\text{Я}_{(\mathrm{I})}$ (3)

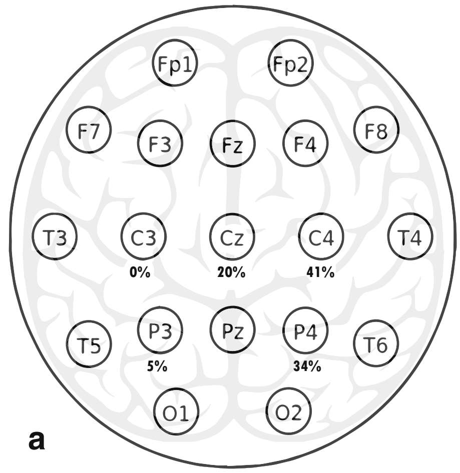


Fig. 4 Feature values indicates for each electrode with/without using activity ratio in a preselected group of electrodes. A) Feature values without activity ratio. B) Feature values with activity ratio

Methods

Proposed method

The aim of this study is to investigate and highlight current challenges in the selection of EEG electrodes. Towards this purpose, a new approach based on a genetic algorithm (GA) is proposed to determine the minimum number of electrodes that provide the maximum accuracy for EEG-based identification. The method does an exhaustive search by picking random groups of electrodes to find its optimal identification accuracy corresponding to specific stimuli, i.e., relaxation during eye-closed (EC) and eye-open (EO). Moreover, the investigation also looked at the relationship between the number of electrodes in such stimulus and standard EEG frequency sub-bands (α, Low-β, High-β, and γ). The four-stage processing model is detailed in Fig. 2. Figure 3 explains the stages of identification process of this study starting from acquiring the brain EEG raw signals, then signal processing stages, till getting the sets of electrodes that suggested by GA corresponding to each frequency sub-bands, and finally the matching process with the stored information of the individuals for making the decision of the identification.

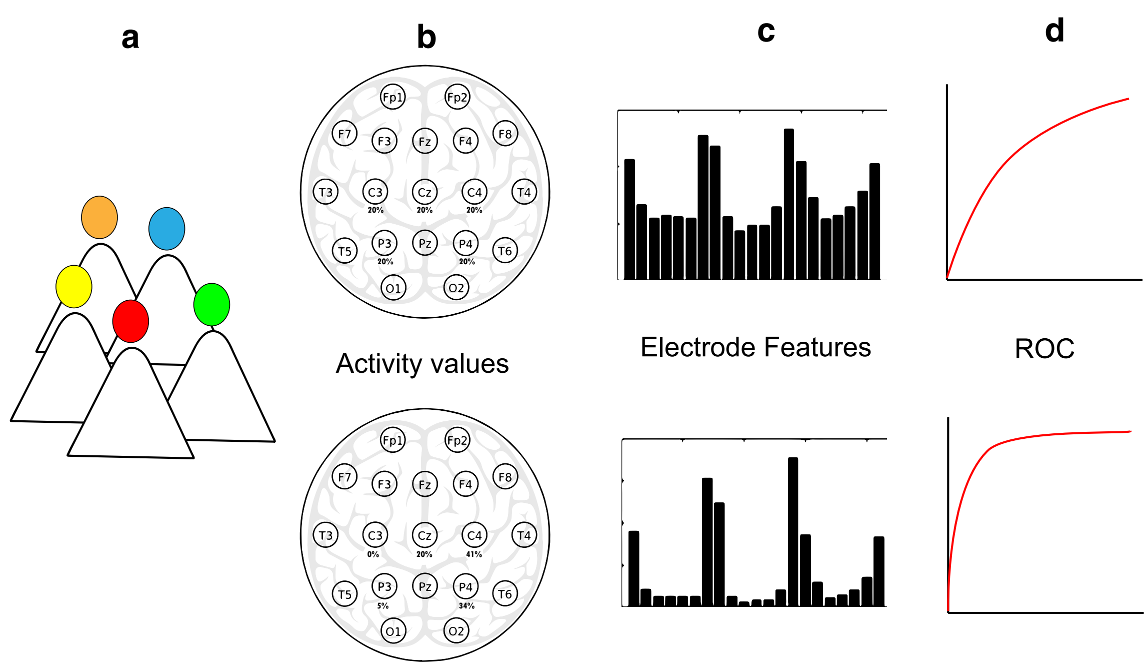


Fig. 5 The differences between classical and enhanced features based on electrodes activity ratio. A) Diversity of individuals' responses to a stimuli. B) The difference between electrodes activity values in the classical method and actual activity values. C) The difference between classical extracted features and enhanced features of each electrode. D) Receiver operating characteristic curve (ROC) of the classification

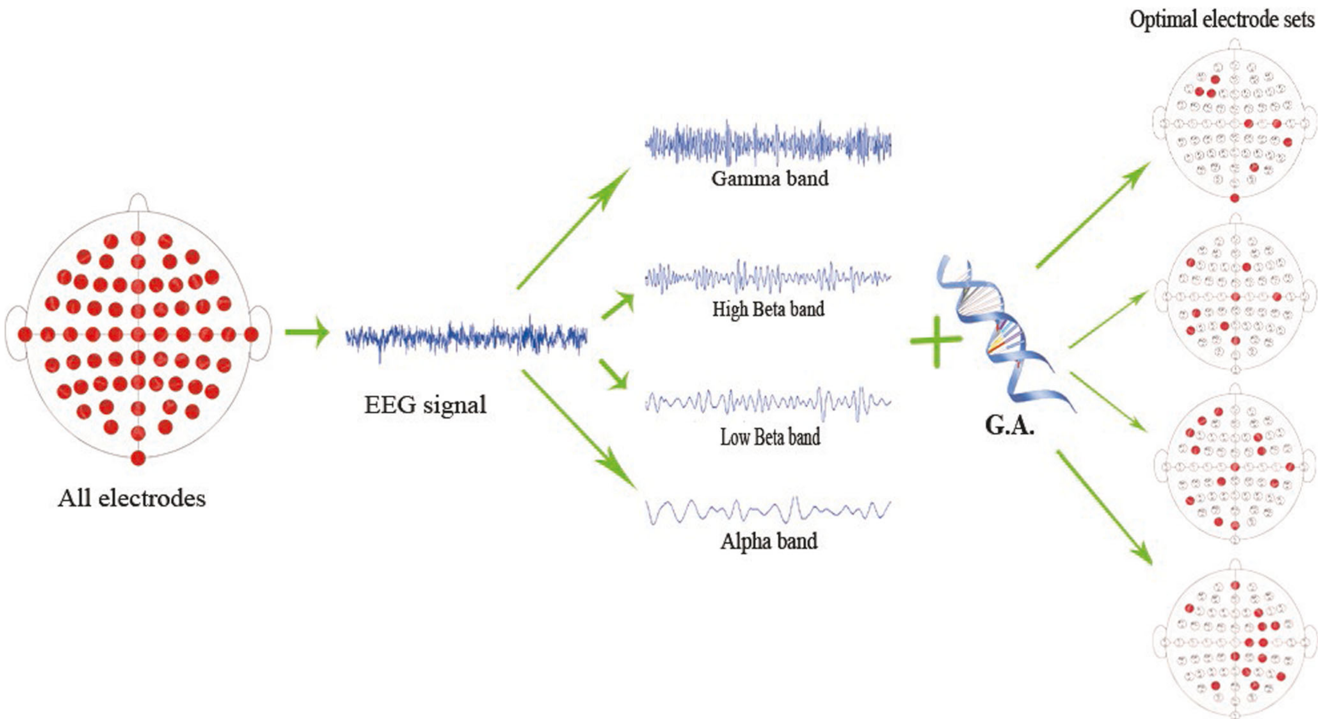


Fig. 6 The active electrodes of EO stimulus corresponding to each frequency sub-band suggested by GA

Dataset

This work utilized a publicly available EEG dataset described in [15] that is available for download (https://physionet.org/pn4/eegmmidb/). The dataset consists of EEG signals obtained from 109 volunteers. The recording was done for two EO-EC resting tasks of 60 s each, while a 64-channel EEG device recorded using the BCI2000 system. All subjects of this dataset were used to test the proposed method based on characteristics relevant to identification taken from other published studies [11, 16–20].

Pre-processing

The pre-processing phase enhanced the signal-to-noise ratio and improves signal quality without losing information. The first step extracted related events in the data and discarded other unneeded events. Independent component analysis (ICA) was then applied to remove artifacts of the eye and heart that was in the raw data. Subsequently, the data was segmented into 60s blocks to extract five relevant epochs of 12 s each. This period was used in studies [16, 18, 20]. Also, the EEG channels referenced an ear electrode, i.e., T9 electrode (common reference montage), the reason behind this selection

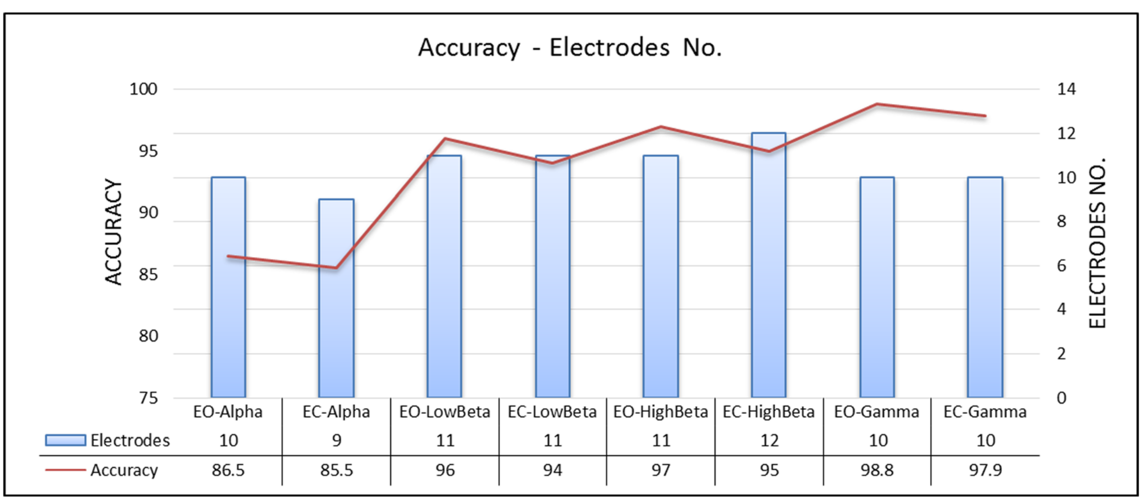


Fig. 7 Optimum identification accuracy results shows in all stimulus based on the number of electrodes

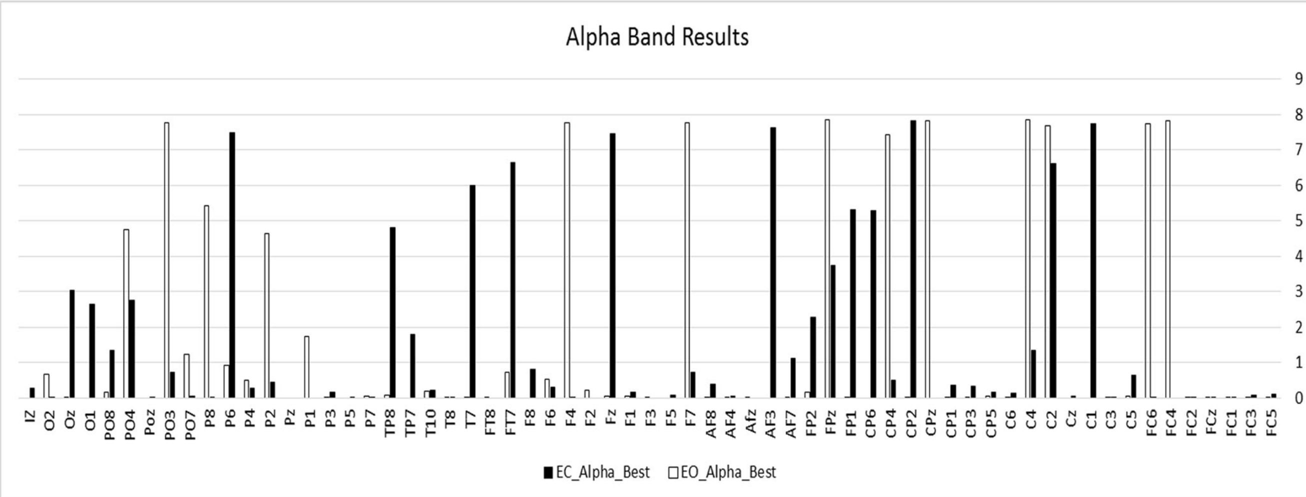


Fig. 8 Active electrodes appears in Alpha band with relaxation EC & EO stimuli

being because ear electrodes are less affected by external and internal artifacts. Therefore, the total selected electrodes were 63 electrodes. Finally, the sample rate was 160 samples per second as in [16]. Testing was done using a personal computer running Windows 8.1 with a 64-bit, CPU Core-i7, 2.3 GB, RAM 8 GB DDR3, and GPU of 4 GB.

Feature extraction and classification

There are several techniques to extract EEG signal features after the pre-processing phase. The type of selected features is beyond the scope of this study. Consequently, the selected statistical features adopted for extracting relevant feature vectors were: mean, standard deviation (SD), and power as shown in Table 1. The selected features were the same as study [21], which also used EEG signals for identification.

To cover the variety of subject responses to chosen stimuli and to make active electrodes more distinguishable, we dynamically assigned weights (values) for each electrode to determine its activity level while doing a mental task. The assigned values mainly depend on the signal-energy provided by that electrode. Hence, the electrode energy value can be used to obtain the activity ratio of each electrode as shown in Fig. 4. Then, this ratio was multiplied by the values of extracted features for each electrode individually. This procedure increases the dependability of the electrodes. Hence, electrodes with high activity will surmount those of low activity corresponding to their activity ratio (energy). Adopting this algorithm may also help in solving the activity diversion problem of electrodes that exist among individuals, as mentioned in [22], because it will minimize or maximize the values of the extracted features of each electrode individually

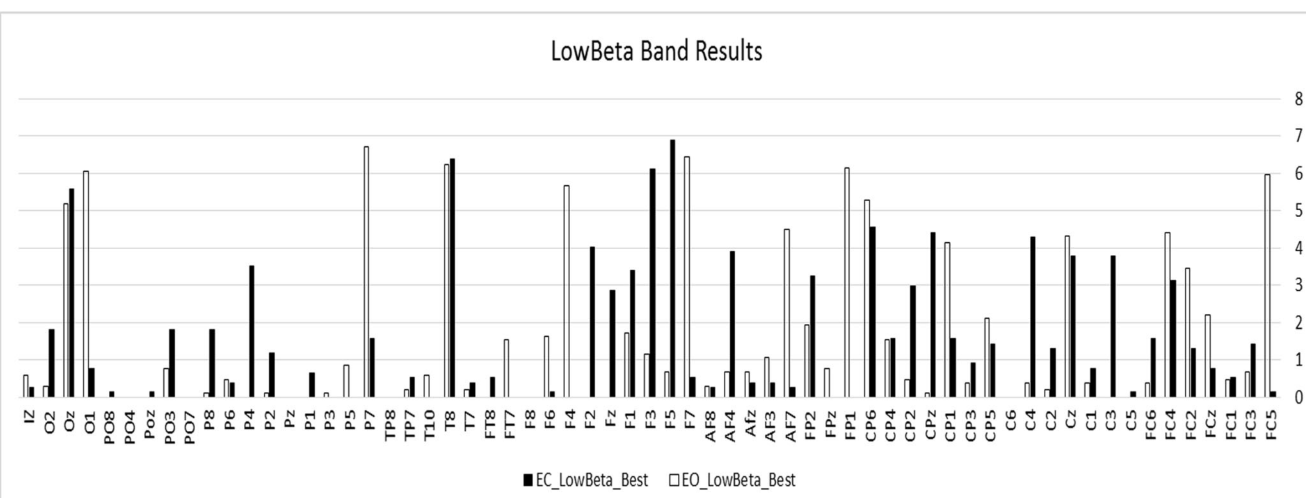


Fig. 9 Active electrodes appears in Low-Beta band with relaxation EC & EO stimuli

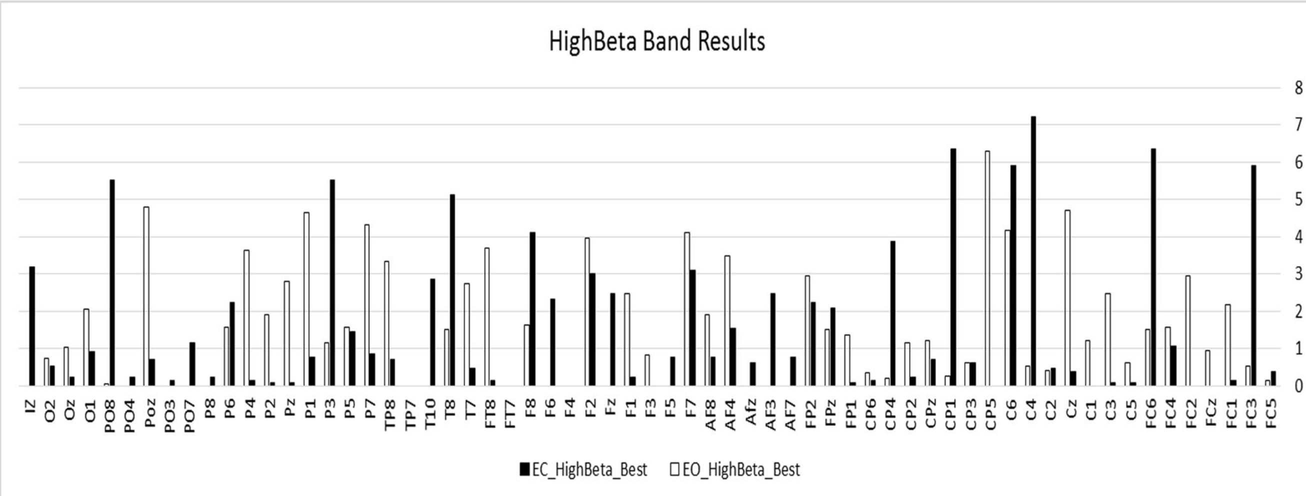


Fig. 10 Active electrodes appears in High-Beta band with relaxation EC & EO stimuli

rather than discarding or selecting them. The differences between processing the features in classical way and the proposed feature enhancing method shown in Fig. 5.

$$Z_{(l)} = \left(\omega_{1(l)}, \omega_{2(l)}, \ldots, \omega_{k(l)}\right) \tag{4}$$

$$E_{(l)} = \sum_{i=1}^{N} |Ai|^2 \tag{5}$$

$$Z\text{Я}_{(l)} = E_{(l)} / \Sigma^{n}_{i=1} E_{(l)} \tag{6}$$

$$Z`_{(l)} = Z_{(l)} \times Z\text{Я}_{(l)} \tag{7}$$

Where:

n = No. of electrodes; l = lectrode; ω = feature; k = No. of features; E = energy equation; N = data length; $Z_{(l)}$ = set of all features; $Z\text{Я}_{(l)}$ = activity ratio based energy; $Z`_{(l)}$ = new set of all features.

EEG signals consist of five major bands. For each individual, the energy distributions of the frequency components are quite different and, thus, this makes it possible to adopt these frequency components as features to represent the EEG signals of a particular person [23]. A typical adult EEG signal is about (10–100 μV) when measured from the scalp [24]. These signals show fluctuations roughly in the frequency range from 0.5 Hz to 100 Hz, and fundamentally in the range from 0.5 Hz to about 50 Hz [25]. This range can further be divided into different frequency sub-bands, i.e., 0.5–4 Hz (Delta, δ), 4–8 Hz (Theta, θ), 8–13 Hz (Alpha, α), 13–30 Hz (Beta, β) and > 30 Hz (Gamma, γ) [25, 26]. Further, the Beta band can be divided into two sets, Low-Beta (L-β) and High-Beta (H-β). These bands are correlated to different cognitive status. The acquired signals filtered using a band-pass filter (BPF) correspond to these basic bands in order to investigate the best accuracy and minimal number of electrodes in each band. This partitioning was also used in [11, 16, 18, 20].

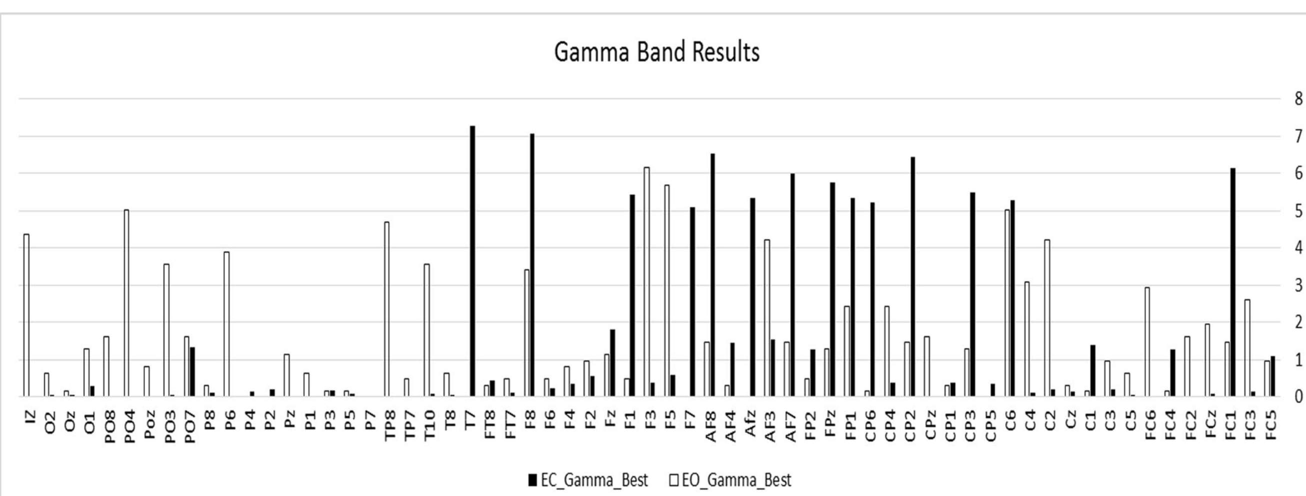


Fig. 11 Active electrodes appears in Gamma band with relaxation EC & EO stimuli

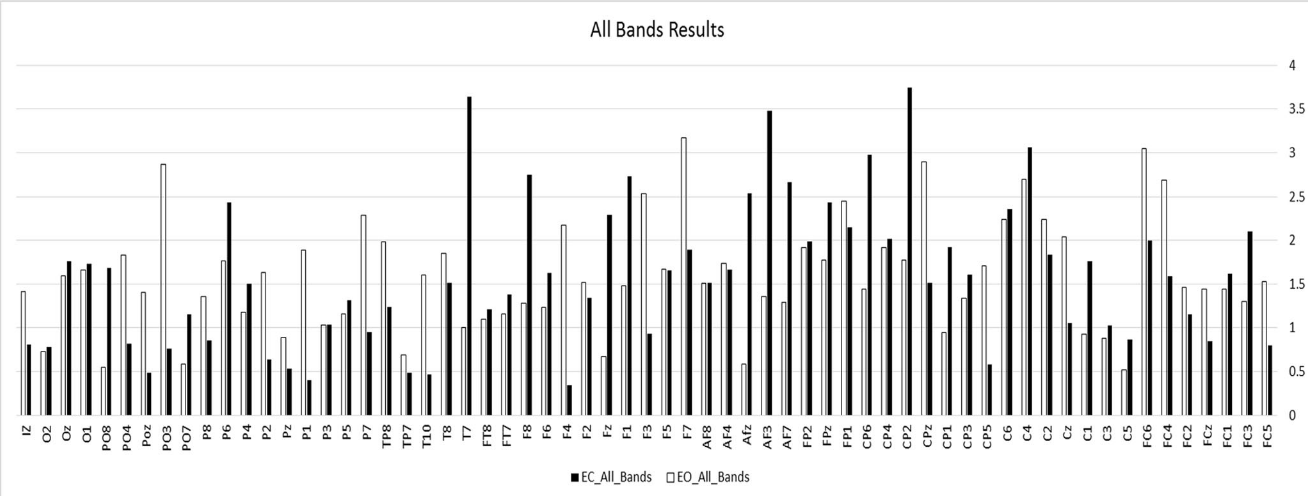


Fig. 12 Active electrodes appears in all bands with relaxation EC & EO stimuli

Where: N = number of electrodes.

An accurate feature extraction method is fundamental for extracting useful features from original signals that would significantly affect the accuracy of EEG signal classification. There are a huge number of classifiers that may help to address the results of a system. However, comparing the different results of these classifiers is beyond the scope of this study. Nevertheless, SVM classifiers provide better results with more high-density data [27]. This study used a Fine-Gaussian SVM algorithm inside a GA fitness function to test the accuracy of active electrodes provided by GA functions in each iteration.

Genetic algorithm (GA)

This study proposes a genetic algorithm to select the best set of electrodes for identification corresponding to each frequency sub-band as shown in Fig. 6. There are many benefits to reducing the number of electrodes. However, sometimes too many reductions negatively affect classification accuracy. As such, our aim is to find the best combination for a minimum number of electrodes with higher accuracy. We are not claiming that this combination is always the right choice. In fact, sometimes better accuracy is more important than the number of electrodes. Consequently, the objective function of the GA build is to satisfy these two conditions as shown in Algorithm 1 and (B) of Fig. 2. The population type is set to a binary format where one represents an electrode that is on and zero means it is off.

$$Fitness = Min\left(\frac{acc.}{100} \times sum(e)\right) \tag{8}$$

$$Accuracy\ (acc.) = \frac{\#of\ \ correctly\ classified\ data}{\#of\ \ tested\ data} \tag{9}$$

Where: e = No. of ones generated by GA (selected electrodes).

The inputs of GA were set to the 63 variables that represent the electrodes, which correspond to the chosen DS with one common reference, and two outputs, i.e., the electrode set and its accuracy. A population size of 500 is shown in (III) and (A) of Fig. 2, respectively. Stop criteria determine what causes the algorithm to terminate, as shown in (C) of Fig. 2. The GA

Table 3 List of electrodes and average identification accuracy in different frequency bands

Stimuli	Avg. Accuracy	Electrodes	Electrodes No.
Alpha EO	86.2	FC4, FC6, C2, C4, CPz, CP4, F7, FPz, F4, P2, P8, PO3, PO4	13
Alpha EC	85.3	C1, C2, CP2, CP6, FP2, AF3, F2, FT7, T7, TP8, P6	11
L-Beta EO	95.8	FC5, FC4, Cz, CP1, CP6, FP1, AF7, F7, F4, T8, P7, O1, Oz	13
L-Beta EC	94.1	C3, Cz, C4, CPz, CP6, AF4, F5, F3, F2, T8, Oz	11
H-Beta EO	96.7	Cz, C6, CP5, F7, F2, P7, P1, POz	8
H-Beta EC	95.4	FC3, FC6, C4, C6, CP1, F8, T8, P3, PO8	9
Gamma EO	98.3	C2, C6, AF3, F5, F3, TP8, PO4, Iz	8
Gamma EC	97.5	FC1, C6, CP3, CP2, CP6, FP1, FPz, AF7, AFz, AF8, F7, F1, F8, T7	14

Table 2 comparing with related works based Equal Error Rate (EER)

Stimuli	Bands	Current Study	electrodes	[16] Fraschini et al. (2015)	electrodes	[17] Ma lan et al. (2015)	electrodes	[18] Crobe et al. (2016)	electrodes	[19] Kaur et al. (2017) Best EER	electrodes	[11] Thomas et al. (2017)	electrodes	[20] Fraschini et al. (2018) Best EER	electrodes
EO	α	0.135	10	NA	NA	0.12	NA	0.345	NA	0.019	NA	0.303	19	NA	NA
	Low β	0.04	11	0.144				0.257				0.048			
	High β	0.03	11	0.12				0.172							
	γ	0.012	10	0.044				0.131				0.033			
EC	α	0.145	9	NA		0.14		0.348		0.027		0.152		0.151	
	Low β	0.06	11	0.18				0.24				0.074		0.09	
	High β	0.05	12	0.169				0.173						0.081	
	γ	0.021	10	0.065				0.130				0.037		0.059	

algorithm was set to continue until it reached the 20th generation, as done in [13, 28]. The remaining features of the GA were as follows. Fitness scaling chose individuals with the highest fitness values equally. The parents selection of the next generation is a roulette method where the area of each segment is proportional to its expectation. A random single point crossover that combines two parents was selected to form a new individual (or child) for the next generation. A mutation that provides genetic diversity and enables the genetic algorithm to search a broader space was set to 0.01. Finally. a fine Gaussian SVM as described in section 2.4 was used to classify the accuracy of each set of inputs (variables) provided by the GA. The GA features mentioned above are shown in (D), (E), (F), (G), and (H) of Fig. 2, respectively.

Results and Discussion

Testing the accuracy of all possible electrodes sets in a normal size DS using 64 channels required an excessive amount of time and computational cost as shown in eq. (10). Therefore, GA represents a suitable technique to reduce the number of EEG electrodes required to gain good classification accuracy with less time.

$$\begin{aligned}&(64/64)*(63/64)*(62/64)*\ldots*\\&\mathrm{Or}\left(64!/64^{64}\right)\\&\text{In general}\left(\mathrm{N}!/\mathrm{N}^{\mathrm{N}}\right)\end{aligned} \tag{10}$$

The results of this study were very encouraging. Tests of the GA were repeated for five runs in each sub-band. The best identification accuracy result reached 98.8% and appeared in the *Gamma* band while the eye was open. In general, relaxation with an eye-open stimuli showed better identification accuracy comparing with relaxation with eye-closed stimuli. Figure 7 shows the optimum results of this experiment. Examples include: in EO Alpha 86.5% with 10 electrodes, in EC Alpha 85.5% with 9 electrodes, in EO Low-Beta 96%, EC Low-Beta 94% and EO High-Beta was 97% with 11 electrodes each, in EC High-Beta 95% with 12 electrodes, and in EC Gamma 97.9% with 10 electrodes. The best results with a minimum electrode number ranged between 9 and 12 electrodes, with an accuracy of between 94% and 98.8%. Therefore, the best average identification accuracy results with the number of electrodes less than 14 were chosen as shown in Figs. 8, 9, 10, and 11. In these figures, the X-axis represents the electrodes and Y-axis represents the activity percentage. These figures show the corresponding sets of active electrodes that provide higher accuracy for each particular EEG frequency sub-band. Selecting an EEG sub-band is more efficient and provided better results. As is shown in Fig. 12, the multi-band (all ranges of EEG frequency) made most

Table 4 Accuracy results of proposed energy ratio method with and without electrodes reduction using GA and the new dataset

Sub-Band	Energy Ratio	Energy Ratio using GA	Electrodes No.	Electrodes Name
ALPHA	91.33	90.67	11	F7, F3, FC5, T7, P7, O1, O2, T8, FC6, F4, and F8
L-BETA	96	95	10	F7, F3, T7, P7, O1, O2, T8, FC6, F4, and F8
H-BETA	98.5	98.17	9	F7, F3, FC5, T7, O1, O2, T8, F4, and F8
GAMMA	99	98.5	10	F7, F3, FC5, T7, O1, O2, P8, T8, F4, and F8

electrodes active compared with the selection of one band where the number of active electrodes is fewer.

The relation between the electrodes and the frequency bands is one of the objectives of this study. We observed that it is possible to identify the subjects in these stimuli, even while reducing a considerable amount of information (electrodes) and frequencies (sub-bands). Moreover, even when selecting only one stimulus, a lower number of electrodes could provide the same (and sometimes higher) accuracy compared with a large number of electrodes. The average minimum number of electrodes that provided good accuracy was 10 electrodes out of 64. Additionally, a specific set of electrodes repeated in every iteration and is related to a particular band, as listed in Table 3. These sets of electrodes can be adapted to provide good identification accuracy corresponding to targeted EEG bands in future work.

Electrode activity is analyzed thru patterns. As a result, the effective electrodes used for identification are a combination of either idle electrodes or those mostly located in the central region of the brain, as shown in Table 3. Additionally, higher frequencies provide acceptable average identification accuracy with a fewer number of electrodes compared with lower frequencies. As shown in Table 2, this conclusion is similar to and confirms related studies. Further, Table 2 shows that the proposed genetic algorithm-based method is effective in reducing the number of electrodes while also increasing the accuracy of EEG-based identification.

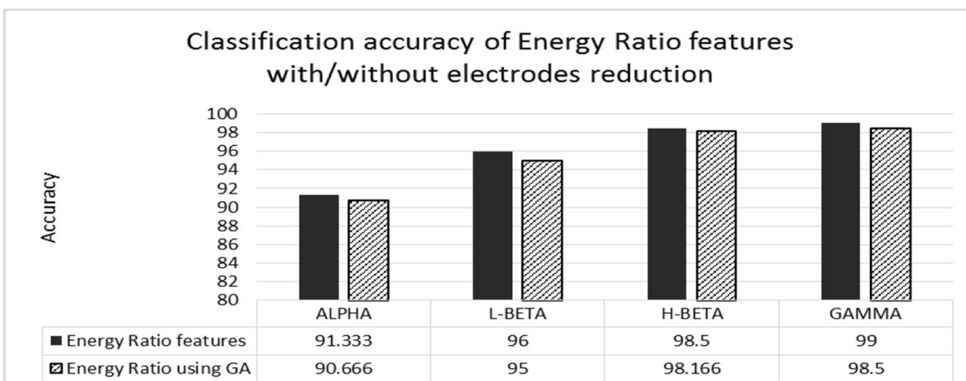


Fig. 13 accuracy results of proposed energy ratio method with and without electrode reduction using GA and the new dataset

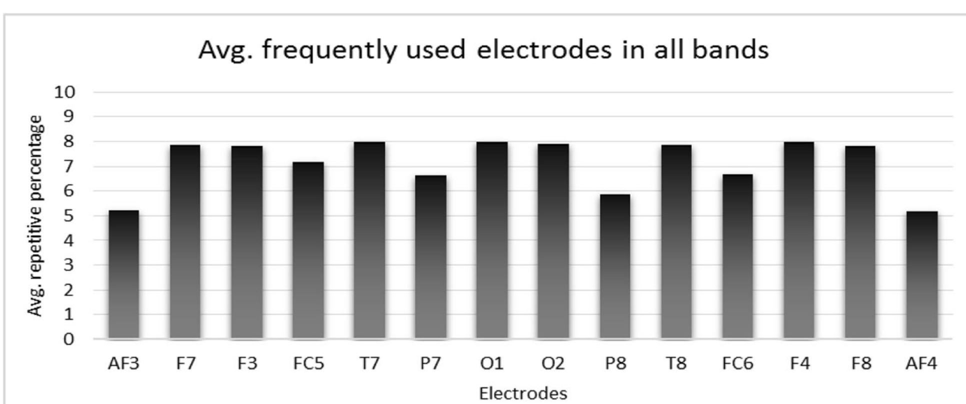


Fig. 14 Average repetitive percentage of each electrode in all frequency bands of the new dataset using proposed energy ratio method and GA

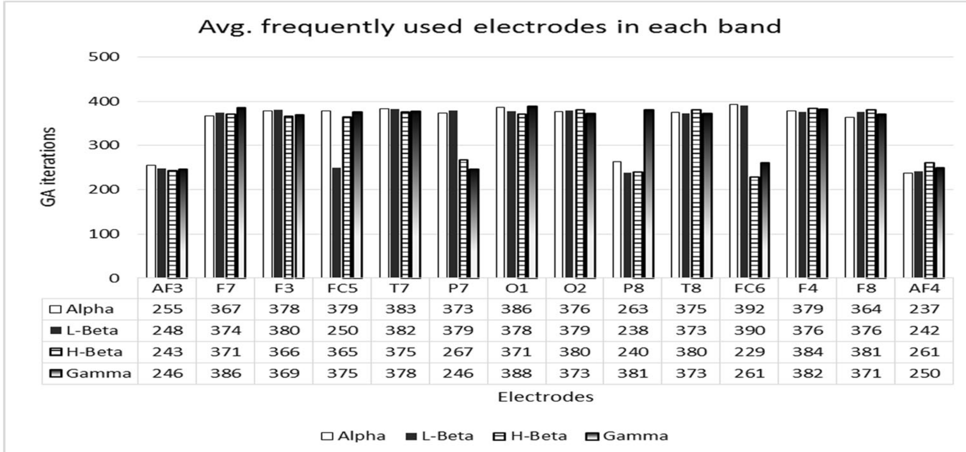


Fig. 15 Average frequently used electrodes in each frequency sub-band using GA with 500 iterations of the new dataset

A new public dataset was created in order to find out whether the proposed methods mentioned in this article can enhance the accuracy results of other datasets with different stimuli and different group of electrodes. EEG Data of 30 subjects was acquired using EMOTIV EPIC+ device of 14 channel using mixed stimuli (Relaxation & concentration) as detailed in [29] . The test was done twice, with and without electrode reduction using GA where the results came very encouraging as shown in Table 4 and Figs. 13, 14, 15.

Conclusion

This study utilized a genetic algorithm (GA) to reduce the number of EEG electrodes required for identification with maximum accuracy. We utilized a public EEG dataset with 109 subjects that has been used in several studies looking at identification. This dataset used 64 electrodes, which was ideal for conducting experiments with the proposed method. The frequency of EEG data was filtered to the basic EEG sub-bands (Alpha, Low-Beta, High-Beta, and Gamma). Similar to past works, we looked at statistical features such as mean, standard deviation, and power. Moreover, an activity ratio method was applied upon the values of selected features for each electrode to enhance these features. Meanwhile, the classification phase was done using SVM algorithm.

The results showed that the proposed method provides better accuracy compared with related works. Moreover, the experiment showed that although using a fewer number of electrodes does not reduce the amount of processing, it may provide better accuracy compared to using the whole set. Each EEG sub-band was tested individually to obtain optimal results. Thereafter, the most reliable sets of electrodes related to each sub-band were obtained. Also, the most efficient sets of electrodes are those less affected by the stimulus or in the central region of the brain. Additionally, the ability to identify subjects increases with a frequency increase, such as with High-Beta and Gamma, and the number of electrodes decreased. Further testing is needed to examine different types of features, mental tasks, and other purposes, such as for clinical assessment. Further, we recommend checking the efficiency of proposed methods using new datasets of a different group of electrodes and stimuli other than the ones tested in this article.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent None.

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