

Article

EEG Channel Selection Based User Identification via Improved Flower Pollination Algorithm

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Abstract: The electroencephalogram (EEG) introduced a massive potential for user identification. Several studies have shown that EEG provides unique features in addition to typical strength for spoofing attacks. EEG provides a graphic recording of the brain's electrical activity that electrodes can capture on the scalp at different places. However, selecting which electrodes should be used is a challenging task. Such a subject is formulated as an electrode selection task that is tackled by optimization methods. In this work, a new approach to select the most representative electrodes is introduced. The proposed algorithm is a hybrid version of the Flower Pollination Algorithm and β -Hill Climbing optimizer called FPA β -hc. The performance of the FPA β -hc algorithm is evaluated using a standard EEG motor imagery dataset. The experimental results show that the FPA β -hc can utilize less than half of the electrode numbers, achieving more accurate results than seven other methods.

Keywords: EEG; biometric; β -hill climbing; flower pollination algorithm; feature selection; auto-repressive



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1. Introduction

Over many years, our world has transferred into a digital community, where each subject lives with a unique digital identifier [1]. Indeed, there are many identifiers, such as identification passwords and cards. At the same time, these identifiers can be easily circumvented, stolen, and forgotten [2]. Therefore, personal characteristics or behaviors can be used to strengthen identification applications. Such techniques, so-called biometrics, use several in-person information to allow more robust identification systems, such as face and voice recognition, fingerprint information, and iris data, among others [3].

On the other hand, the widespread and influential deployment of biometric systems leads to a new challenge, which is called “spoofing” [1,4]. Such an attack is classified as the

most dangerous in security systems since it is designed to break the biometrics systems' security, thus allowing unwarranted persons to obtain admission to the system [2].

In real life, there have already been several spoofing attacks on biometrics systems, such as face spoofing (printed photos and 3D mask attacks [5,6]), fake fingerprints (gummy fingers), finger-vein systems fooled through a piece of paper [7], iris recognition systems fooled by an eyeball opposite to the scanner of iris, and voice recognition fooled by replaying a voice recording opposite to the recognition system speaker [7]. Therefore, people are looking for biometric authentication systems that can grant access to a person based on invisible characteristics, thus becoming harder to be attacked by an external threat. In this context, one shall refer to user authentication based on brain signals, which can be captured by the well-known electroencephalogram (EEG) exam [8].

The EEG is a clinical test that places electrodes on the person's scalp to detect the brain's electrical activities, which are further recorded for visualization purposes. Such information reflects the voltage currents inside the brain from ionic flows concerning the neurons' activity [2]. Approaches to capture electrical brain signals can be categorized as invasive and non-invasive [9], where the former ones require surgery to embed electrodes in the brain. The electrocorticography brain-computer interface (ECoG BCI) is an example, which is usually intended for recording the movements of the arm [2]. Other signal types are used in the non-invasive approaches, such as functional magnetic resonance imaging and magnetoencephalography.

Many studies have proposed to solve issues relevant to identification in biometric applications. For instance, Jayarathne [10] gathered signals as a biometric approach from 21 test subjects to verify their identity. The authors employed the EMOTIV EEG Headset with 14 channels. The Common Spatial Patterns were used for feature extraction and Linear Discriminant Analysis for classification purposes. The proposed approach achieved a 96.97% recognition rate, which motivated the authors to claim that EEG signals might be an excellent approach to replace PINs when accessing ATMs. However, the selection of relevant channels that produces the optimal subset of EEG features is of prime importance for (i) reducing computational complexity, (ii) reducing over-fitting, and (iii) eliminating inconveniences during clinical application [11]. Table 1 presents some studies we thought might be relevant to EEG channel selection.

According to Table 1, many studies have worked on the channel selection problem with different methodologies such as Common Spatial Patterns, optimization, Pearson correlation coefficient, and additional connectivity metrics. Most existing works were implemented based on the data extracted from 64 EEG channels. Furthermore, most works reduced the number of channels and presented significant classification accuracy. In contrast, refs. [10,11] reported good classification performances, but the number of selected channels is still high. On the other hand, some studies have reduced channels up to 50%, but with a moderated classification rate.

Recently, several researchers proposed the use of optimization approaches to solve challenges with non-stationary signals [1,6,12,13]. In addition, EEG-based user identification with supervised classification and optimization methods has shown significant improvements compared to traditional techniques [2,14,15].

Table 1. Some relevant works related to EEG channel selection.

Work	Approach	Case Study	Channels	Selected	Accuracy
Rodrigues et al. [1]	Binary Flower Pollination with OPF	Person Identification	64	45	86%
Fraschini et al. [16]	Different connectivity metrics	Person Identification	64	N/a	N/a
Gaur et al. [17]	Person correlation coefficient	Motor Imagery	118	36.58	78.08%
Kaur et al. [11]	Principal Component Analysis	Person Identification	64	64	97.73%
Idowu et al. [18]	Modified Particle Swarm Optimization	Motor Imagery	64	30.4	91.89%
Jayarathne et al. [10]	Common Spatial Patterns	Person Identification	14	14	96.97%

Signal acquisition is one of the significant problems concerning the EEG-based user identification technique, which is performed by placing electrodes on the head of a human [19–21]. In addition, such a process is usually uncomfortable since it requires good knowledge to place the sensors correctly. Additionally, some questions must be considered: “Is it essential to place all these electrodes on the head of persons?” and “Whether not, may we detect the most significant ones for user identification and then utilize fewer electrodes?”.

The above questions led our work to model the EEG channel selection as an optimization problem. Flower Pollination Algorithm (FPA) is a robust optimization method and has been successfully applied to many real-world problems [22]. Although FPA has proved to be a great success in finding optimal solutions to many issues, it suffers, like metaheuristic algorithms, from the inability to generate new solutions when it is stuck in local minima [23]. According to [1], the authors tested several meta-heuristic algorithms for EEG channel selection, with FPA achieving the most accurate results. However, it still has some problems, such as being stuck in local minima. For this reason, we propose to hybridize FPA with the local search optimizer β -hill climbing (β -hc) [24].

This work is one of the first to employ hybrid optimization methods with supervised classification methods for biometric user identification using EEG. The main point of hybridizing any two approaches is to complement their advantages and avoid their shortcomings. This work aims to learn the most critical EEG channels by proposing a hybrid approach composed of β -hc and FPA, named “FPA β -hc”. Therefore, we expect to obtain more accurate results when applying optimization approaches to select optimal EEG channels. The main contributions of this work are summarized as follows:

1. To evaluate the proposed FPA β -hc for EEG-based user identification. Such a hybrid approach aims to improve local pollination in FPA to avoid being stuck in local minima.
2. To perform an extensive study to select the most suitable classifier to guide the optimization process using FPA β -hc. Our experiments showed that Support Vector Machines with Radial Basis Function (SVM-RBF) obtained the most effective results, thus being the preferred approach in this work.

The remainder of this article is organized as follows: Section 1 presents the main concepts regarding EEG signals, as well as related works about EEG-based identification. The proposed method is detailed in Section 2. The results are discussed in Section 3, the discussion is provided in Section 4, and the conclusions and future works are set out in Section 5.

2. Proposed Method

This section provides a detailed explanation of the proposed approach for EEG channel selection through FPA β -hc, which comprises five steps such that every stage’s output acts as an input to the other one. The proposed approach is depicted in Figure 1.

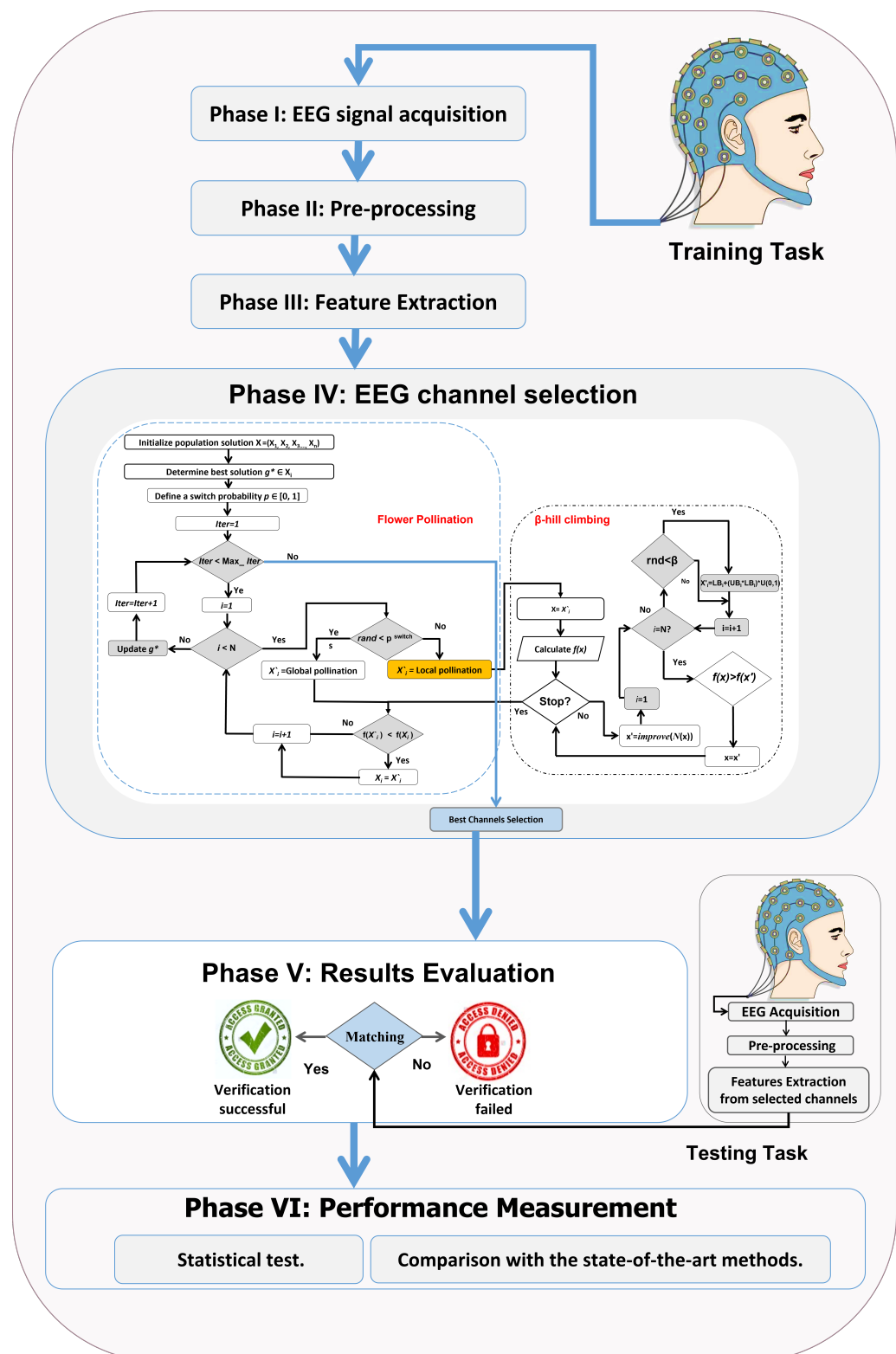


Figure 1. Proposed EEG-based user identification system using FPA β -hc.

2.1. EEG Signal Acquisition

The EEG signal acquisition step is carried out over a typical EEG signal dataset. By using a brain–computer interface software called the BCI2000 system, the EEG signals are gathered from 109 healthy persons [25]. The EEG signals are acquired from 64 electrodes (i.e., channels), and 12 motor/imagery tasks are performed by every subject (i.e., 12 EEG signals records for each individual). Furthermore, AR features with three different numbers

Notably, not all features are helpful for final decisions. Some of them will increase the complexity or will lead to achieving high miss-classification rates. We model the problem of selecting proper AR features as an optimization problem using the objective function defined in Section 2.4, where the channels that achieved the best results are the ones that will be selected.

2.4. Objective Function

Since the proposed method is initially designed to handle continuous-valued optimization problems, we need to map each possible solution onto a binary-valued position, for the EEG channel selection problem requires encoding each possible solution as a binary vector, where ‘0’ means the channel will not be selected and ‘1’ otherwise [1]. To restrict binary solutions only, we need to use the so-called “transfer function” Z , which refers to the Z -shaped transformation function. The primary purpose of using a transformation function is to convert a real-valued solution to another one with binary values suitable for the channel selection problem. This transformation function has been used in [1], where Z can be defined as follows:

$$Z(f(s_i^t)) = \begin{cases} 1 & \phi > \sigma(f(s_i^t)) \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where

$$\sigma(f(s_i^t)) = \frac{1}{1 + e^{-f(s_i^t)}}, \tag{2}$$

and $\phi \sim U(0,1)$. Figure 4 illustrates how to build such a binary vector and to select the optimal EEG subset channels using the proposed $FPA\beta$ -hc.

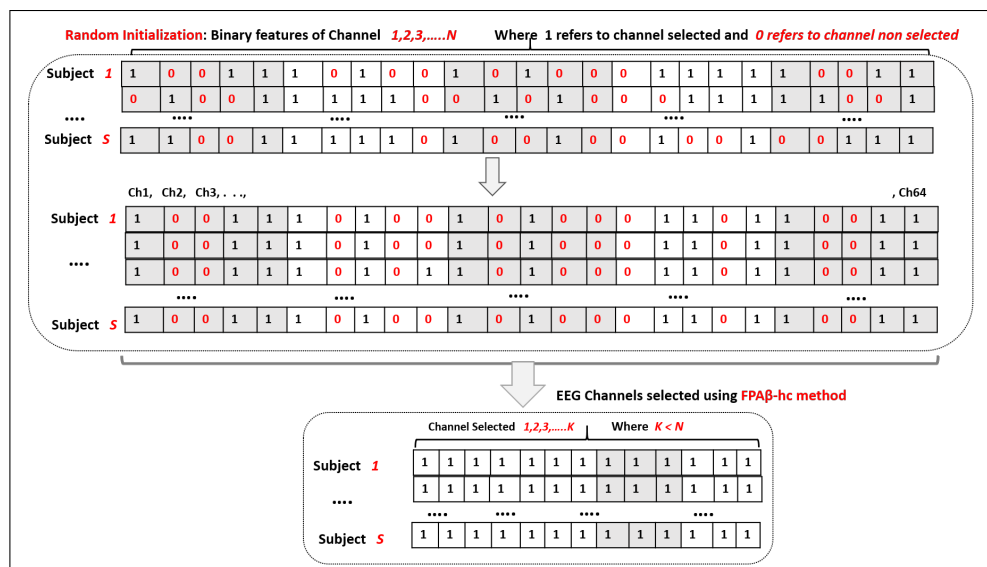


Figure 4. EEG channel selection using the proposed approach ($FPA\beta$ -hc).

Three steps must be considered when selecting the optimal subset of channels. First, a random initialization of the binary vector (representing the EEG channels) is conducted, where ‘1’ refers that a given channel will be selected, and ‘0’ denotes that the channel will not be selected. Second, the $FPA\beta$ -hc starts searching the space to find the optimal subset of channels, i.e., the one that can provide the highest accuracy rate based on Equation (3). Finally, we discard all channels with ‘0’ values and keep the remaining ones.

The objective function used to evaluate the classification performance of EEG channel selection is formulated below:

$$Acc = \frac{TA + TR}{TA + FA + TR + FR} \times 100 \quad (3)$$

where Acc denotes the objective function (accuracy rate) calculated for each row of the AR feature matrix, and TA , TR , FA , and FR represent the true acceptance, true reject, false acceptance, and false reject rates, respectively.

Algorithm 1 presents the proposed method that employs BFPA β hc for EEG-channel selection using the SVM-RBF classifier and Equations (1) and (2) as the transfer function.

Algorithm 1 Hybridizing Flower Pollination Algorithm with β -hill climbing for EEG Channels Selection.

```

1: Input
2: Initialize a population of  $N$  flowers/pollens with random solution
3: Find the best solution  $G_{sol}^*$  in the initial population
4: Define a switch probability  $p \in [0, 1]$ 
5: Channels =  $\{Ch_1, Ch_2, \dots, Ch_D\}$ 
6: for  $a = 1$  to  $N$  do
7:   Evaluate fitness value of  $f(sol)$  based on 10-fold-C5V SVM and Accuracy rate of EEG Channels Selection [Equation (3)]
8: end for
9: Find  $G_{sol}^*$ , where  $G_{sol}^* \in (1, 2, \dots, N)$ 
10:  $itr = 0$ 
11: while  $itr < Total\_iterations$  do
12:   for  $j = 1$  to  $N$  do
13:     for  $i = 1$  to number of channels( $D$ ) do
14:       if  $rnd \leq p$  then
15:         Draw a ( $d$ -dimensional) step vector  $L$  which obeys a Levy distribution
16:         Global pollination via  $sol_i^{itr} = sol_i^{itr-1} + L * (G_{sol}^* - sol_i^{itr-1})$ 
17:          $sigmoid(sol_i^{itr}) = \frac{1}{1 + e^{-sol_i^{itr}}}$ 
18:         if  $sigmoid(sol_i^{itr+1}) > U(0, 1)$  then
19:            $sol_{i,j}^{itr} = 1$ 
20:         else
21:            $sol_{i,j}^{itr} = 0$ 
22:         end if
23:       else
24:         Draw from a uniform distribution  $\in [0, 1]$ 
25:         Randomly choose  $j$  and  $k$  among all solution
26:         Do local pollination via  $sol_i^{itr} = sol_i^{itr-1} + \epsilon (sol_j^{itr} - sol_k^{itr})$ 
27:          $sigmoid(sol_i^{itr}) = \frac{1}{1 + e^{-sol_i^{itr}}}$ 
28:         if  $sigmoid(x_i^{itr}) > U(0, 1)$  then
29:            $sol_{i,j}^{itr} = 1$ 
30:         else
31:            $sol_{i,j}^{itr} = 0$ 
32:         end if
33:       end if
34:     end for
35:     Run  $\beta$ -hill climbing algorithm using  $sol_{i,j}^{itr}$ .
36:     while Stop criterion is not met do
37:        $New - sol_{i,j}^{itr} = \mathcal{N} - Operator(sol_{i,j}^{itr})$ 
38:        $New - sol_{i,j}^{itr} = \beta - Operator(New - sol_{i,j}^{itr})$ 
39:       if  $f(New - sol_{i,j}^{itr}) \leq f(New - sol_{i,j}^{itr})$  then
40:         replace  $(New - sol_{i,j}^{itr})$  by  $(New - sol_{i,j}^{itr})$ 
41:       end if
42:     end while
43:      $sol_{i,j}^{itr} = New - sol_{i,j}^{itr}$ 
44:   end for
45:   Update  $G_{sol}^*$ , where  $G_{sol}^* \in (1, 2, \dots, N)$ 
46:    $itr = itr + 1$ 
47: end while
48: Output
49: Return  $G_{sol}^*$ : best channels subset with highest accuracy rate.
50: End

```

2.5. Experimental Setup

The dataset \mathcal{D} is partitioned into three subgroups, $\mathcal{D} = \mathcal{D}_1 \cup \mathcal{D}_2 \cup \mathcal{D}_3$, which stand for the training, validation, and test sets, respectively. In addition, we decided to use 50% of the dataset for training purposes and 20% and 30% for the test and validation datasets, respectively, as suggested by Rodrigues et al. [1]. We adopted the classification accuracy of a Support Vector Machine with Radial Basis Function (SVM-RBF) over the validation set as the objective function to assist the optimization process. The main idea is to employ training and validation sets to find the subset of EEG features that maximize the classification accuracy over the latter. Finally, we select the best subgroups of channels that provide the highest accuracy rates and train the classifier once more. The final accuracy is assessed over the test set. The experiments have been performed utilizing a Lenovo Ideapad 310 PC, Intel Core-i7 with 2.59 Ghz processor, 8 GB of RAM, and Windows 10. The FPA and FPA β -hc parameter values are presented in Table 2. Notice that T refers to the maximum number of iterations used in the experiments. These parameters have been selected based on our previous works [13,24].

Table 2. Parameter setting up.

Algorithm	Parameters
FPA	$p = 0.8, \mathcal{N} = 64, D = 20$, and $Titr = 100$
β -hc	$\beta = 0.5, \mathcal{N} = 64, D = 1$, and $Titr = 100$

3. Results

This section details the experiments used to evaluate the proposed approach; standard approaches in Section 3.1; comparison against standard FPA, β -hc, and FPA β -hc in Section 3.2; and, finally, comparison with State-of-the-Art in Section 3.3.

3.1. EEG Classification Using Standard Machine Learning Approaches

Eight classifiers are selected from the literature according to their performance in EEG applications and evaluated their effectiveness to guide the optimization process proposed in the work: Linear Support Vector Machines, Artificial Neural Networks (ANN), Optimum-Path Forest (OPF), k -Nearest Neighbors (k -NN), Support Vector Machine with Radial Basis Function, Linear Discriminant Analysis (LDA), Decision Tree (J48), and Naive Bayes. Table 3 presents the parameter setting for these classifiers.

Table 3. Parameter setting up.

Classifier	Parameters
LDA	Preset = Linear, covariance structure = Full
LinearSVM	$C = 1.00 \times 10^{11}$, $\text{Gamma} = 0.01$, Kernel = Linear, Standardize data: True
KNN	Kernel = Fine, Distance weight: Equal, Distance: Euclidean, Standardize data: True
ANN	Hidden layer = 32, Learning Rate = 0.3, binary splits = True
Naivebayes	$C = 0.691$, $\text{Gamma} = 0.95$, binary splits = True
J48	confidence factor = 0.25, binary splits = False, seed = 1
OPF	– –
RBF-SVM	$C = 1.00 \times 10^{11}$, $\text{Gamma} = 0.01$, Kernel = RBF

Since the proposed approach is non-deterministic, we computed the mean accuracy rate over 25 runs for avoiding bias outcomes as used in [1]. To evaluate the proposed approach, we considered five measures: (i) Accuracy (Acc), (ii) Number of selected channels (No. Ch), (iii) Sensitivity (Sen), (v) Specificity (Spe), and (iv) F-Score.

Table 4 presents the performance of FPA β -hc with different classifiers. Regarding AR₅ model, it has been observed that FPA β -hc-SVM-RBF outperforms all methods on all evaluation measurements. The LDA stands out as the second-best approach with the five

3.2. Comparison against Standard FPA, β -hc, and FPA β -hc

After selecting the best classifier for the EEG-based person identification problem (i.e., SVM-RBF), standard FPA, β -hc, and FPA β -hc are compared to select the best one for further comparison with some state-of-the-art techniques. Figure 5 depicts the convergence ratio, and the frequency of chosen electrodes for standard FPA and FPA β -hc for 25 runs during the experimental evaluation using AR-5, AR-10, AR-20, and Wavelet Transform WT.

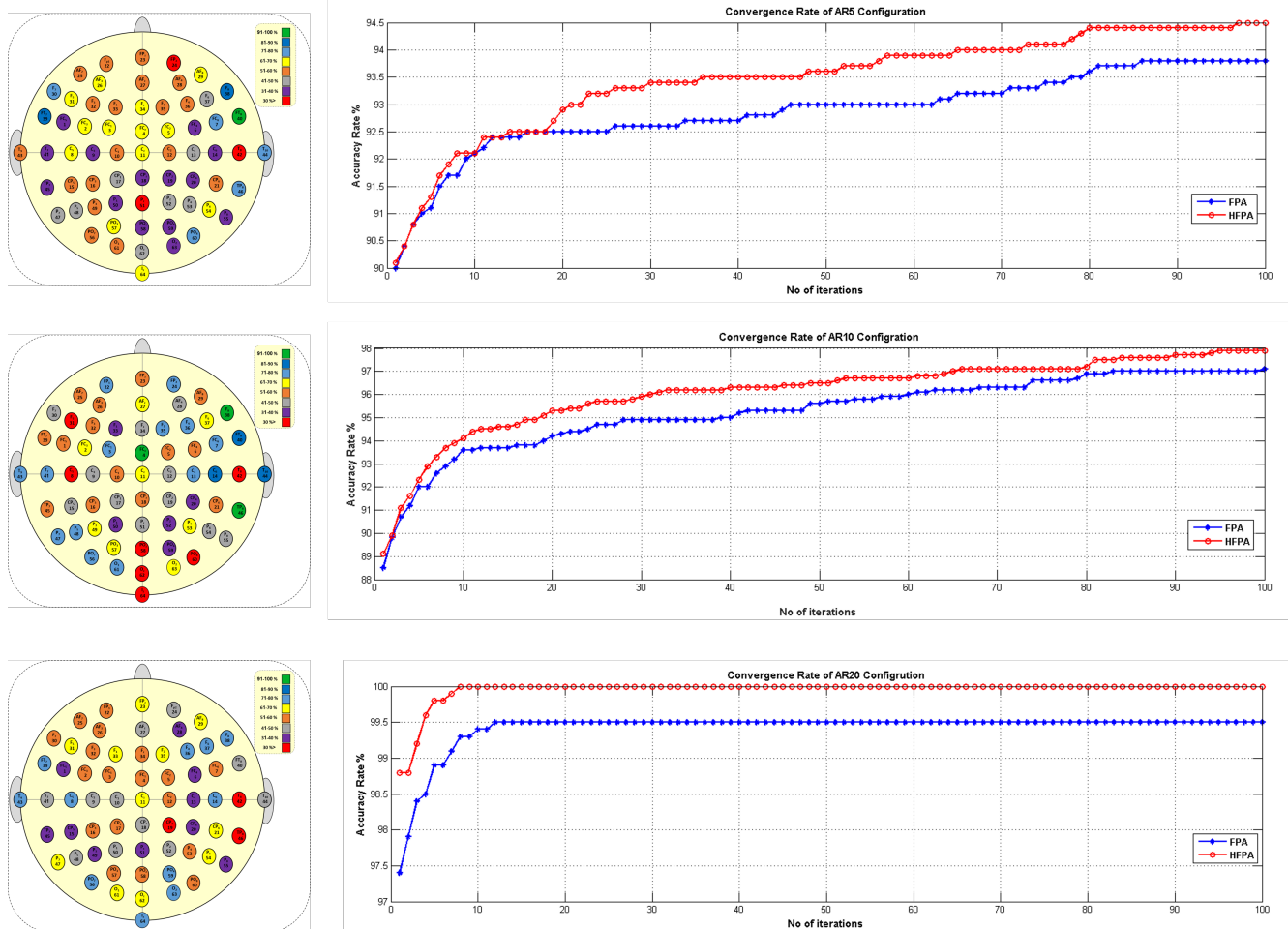


Figure 5. Convergence rate and the frequency of channel selection for FPA β -hc and FPA.

Table 6 presents the overall results concerning the comparison between standard FPA, β -hc, and FPA β -hc. It is clear from the experimental outcomes that the proposed method considerably improves the results considering all auto-regressive coefficients. Regarding the number of selected channels, the proposed approach showed quite good performance. On the other hand, β -hc selected the lowest number of channels, but it yielded worse results than the proposed method concerning the remaining measures (i.e., Acc, Sen, Spe, and F-Score). Even though β -hc obtained the lowest number of channels, it has less classification accuracy when compared with FPA β -hc.

Table 6. Comparison between FPA, β -hc and FPA β -hc.

Dataset	Measure	FPA-SVM-RBF	FPA β -hc-RBF-SVM	β -hc-RBFSVM
AR ₅	Acc	93.3523	94.5619	93.2
	No. Ch	37	34	31
	Sen	0.9395	0.9476	0.928
	Spe	0.9935	0.9943	0.9963
	F-Score	0.93	0.9473	0.929
AR ₁₀	Acc	97	97.9619	94.2667
	No. Ch	40	36	30
	Sen	0.9795	0.9796	0.9422
	Spe	0.9935	0.9943	0.9936
	F-Score	0.97	0.983	0.9412
AR ₂₀	Acc	99.523	100	89.6
	No. Ch	38	35	33
	Sen	0.995	1	0.8899
	Spe	0.9935	1	0.9884
	F-Score	0.995	1	0.8811
WT	EEGAcc	78.1714	79.48	77.2
	No. Ch	33	39	33
	Sen	0.7817	0.7949	0.772
	Spe	0.9757	0.9772	0.9747
	F-Score	0.7727	0.7854	0.7632

The proposed approach provides an excellent compromise between the number of selected channels and the remaining evaluation measurements compared to β -hc. Figure 6 depicts the results considering all measures. Additionally, we conducted the Wilcoxon signed-rank statistical test to check if there is a substantial variance between standard FPA and FPA β -hc. The statistical outcomes are tabulated in Table 7 in terms of P-value, w-value, z-value, and T-Sig. For all experiments (i.e., AR models and WT), FPA β -hc results are significantly better than basic FPA. The proposed FPA β -hc-SVM obtained success in achieving the best results compared with standard FPA and β -hc EEG channel selection. This points out the power of hybridization to complement their advantage and avoid their shortcomings (i.e., FPA and β -hc).

Table 7. Wilcoxon signed-rank test between FPA and FPA β -hc.

Dataset	p-Value	w-Value	z-Value	T-Sig	FPA β hc
AR ₅	0.05	0	−8.329	0.00058	++
AR ₁₀	0.05	72.5	−0.1894	0.008493	++
AR ₂₀	0.05	12.5	−2.3062	0.002088	++
WT	0.05	0	−0.14	0.00334	++

++ indicates a significant inclination to FPA β -hc.

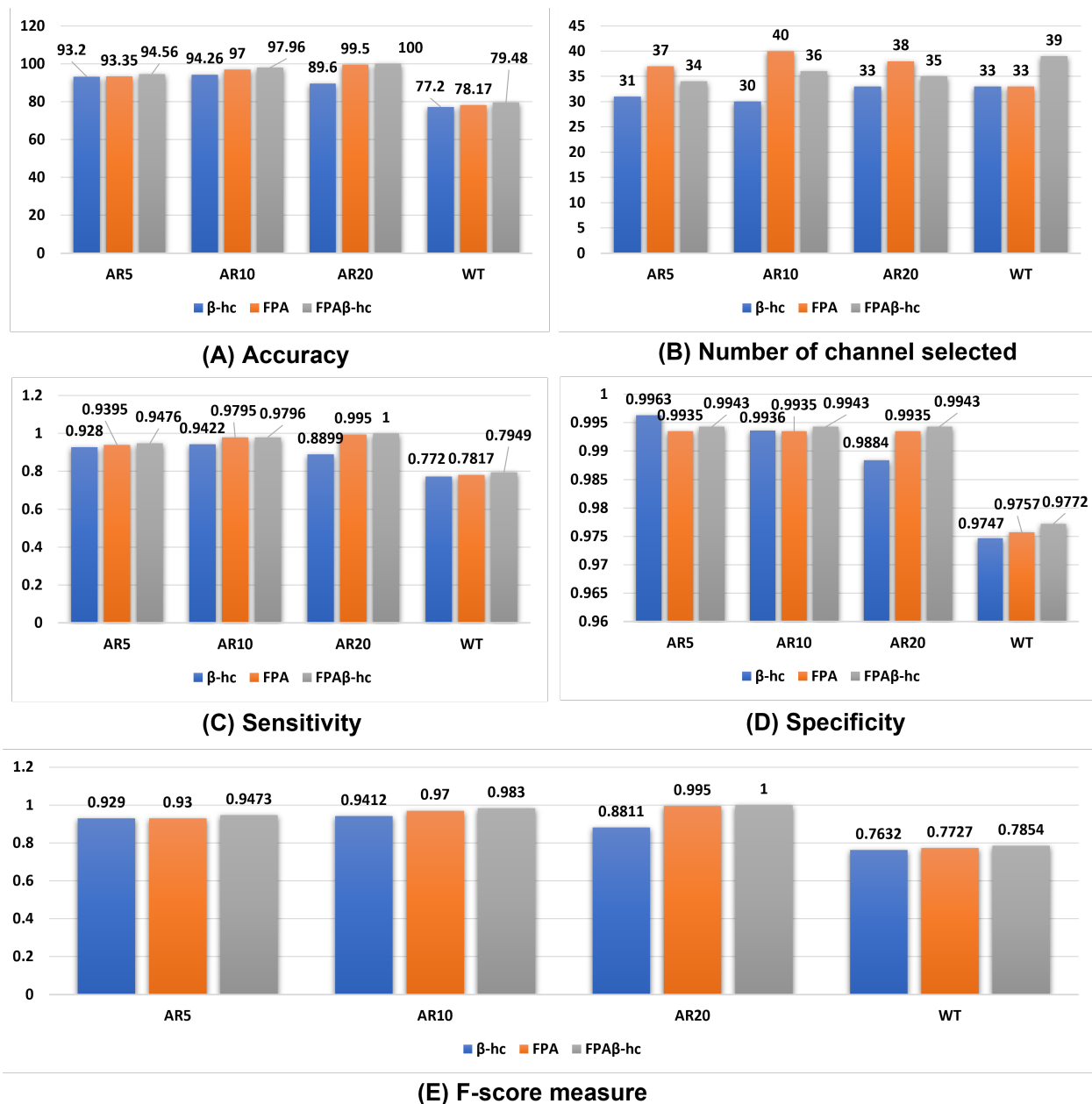


Figure 6. Performance results of the proposed approach over different feature extraction methods.

3.3. Comparison with State-of-the-Art

The proposed FPA β -hc-SVM-RBF is compared against six different state-of-the-art approaches. These methods were carefully selected from the literature, where some are used as a metaheuristic algorithm to select the optimal number of channels: Binary Flower pollination Algorithm with OPF classifier (BFPA-OPF) [1], hybrid FPA with β -hill climbing [2], Genetic algorithm (GA) [26], and a deep learning approach proposed in [27,28]. The comparison involved two criteria, i.e., the accuracy rate and the number of selected channels. The proposed FPA β -hc showed significant superiority in accuracy criteria, achieving 100% of recognition rate. However, concerning the number of selected, it is ranked third. Figure 7 and Table 8 present a comparison of the accuracy rate using the proposed approach against the methods mentioned earlier.

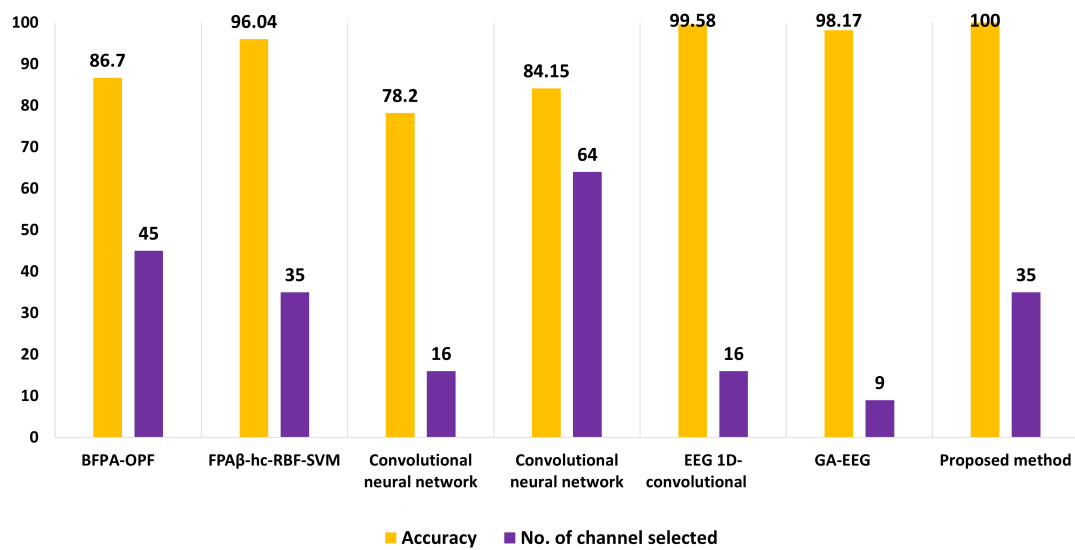


Figure 7. Comparison of the proposed approach with state-of-art methods.

Table 8. Comparison of the proposed method (FPA β -hc-SVM) with state-of-the-art approaches.

Method	Accuracy (%)	No. Ch	Total Channels No.
BFPA-OPF [1]	86.7	45	64
FPA β -hc-SVM-RBF [2]	96.04	35	64
Convolutional Neural Network [27]	78.2	16	64
Convolutional Neural Network [27]	84.15	64	64
EEG 1D-convolutional [28]	99.58	16	64
GA [26]	98.17	9	32
Proposed approach	100	35	64

4. Discussions

As aforementioned, the primary purpose of this study is to evaluate the proposed FPA β -hc-SVM for EEG-based user identification. In this work, we modeled the channel selection task as an optimization problem and introduced the SVM classifier for EEG-based biometric user identification. One can observe the proposed methods achieved similar accuracy rates using SVM considering three different autoregressive coefficients and wavelet features, with an advantage to FPA β -hc-SVM when compared to standard FPA and β -hc optimizers.

Concerning the number of selected channels, FPA β -hc-SVM has succeeded in reducing up to half of the total electrodes. The proposed algorithm reduced the total number of electrodes from 64 to 34, 36, 35, and 39 for AR_5 , AR_{10} , AR_{20} , and WT , respectively. Moreover, we can observe that different AR coefficients provide different accuracy rates regarding the EEG-based person identification task. The proposed approach obtained 100% of accuracy using only 35 sensors and with AR_{20} features.

Another exciting feature of FPA β -hc-SVM concerns the location of the selected electrodes. It is worth noticing that the proposed method showed that the most common sensors are located on the frontal, occipital, and parietal lobes, although they also spread along with the head. Such finding is an interesting observation, which means FPA β -hc-SVM tried to identify channels not too close to each other to obtain relevant details from all over the human brain. Table 6 shows a comparison of the proposed method against some state-of-the-art techniques. It is worth noting that FPA β -hc-SVM achieved the highest accuracy rate when compared to other methods. However, considering the number of selected channels, some improvements are still needed to achieve a minimum number of channels selected, such as the application of multi-objective optimization.

Compared with the previous work, the proposed approach achieved more accurate results using the same feature extraction method (AR₅). The accuracy rate was 93.76%, while the number of channels selected is 32 for the previous work. Here, the proposed method achieved an accuracy rate of 94.56% using 34 channels for the AR₅ features. Overall, the proposed method archived the best accuracy results (100%) with only 35 channels, where the previous work achieved the best results with an accuracy of 96 with the same number of selected channels (i.e., 35 channels).

5. Conclusions and Future Works

In this work, we proposed a hybrid approach composed of the Flower Pollination Algorithm and the β -hill climbing algorithm (FPA β -hc-SVM) to address the challenge of channel selection in EEG-based biometric person identification. The hybrid approach between FPA and β -hc algorithm has been designed to improve the local pollination part of the FPA to overcome local minima. It is worth mentioning that another version of hybrid FPA was also introduced in [2]. However, the main differences between the proposed approach and the previous ones are: (i) the hybridization in [2] is used to enhance the quality of the best-achieved solution, but here, the hybridization is used for local pollination solutions; (ii) the feature extraction techniques used in [2] were time domain, frequency domain, and time-frequency domain, and the feature extraction methods used here are computed by wavelet features and auto-regressive features; (iii) furthermore, in [2], the 10-fold cross-validation method is used for the training–testing stage, while in this study, a training–validation–testing stage is used.

The primary purpose of this work is to demonstrate that all electrodes are not needed to achieve a high accuracy rate. Therefore, this paper is introduced to model the problem of channel selection as an optimization problem. The channel's subset that optimizes the recognition ratio over a validation set is employed as the fitness function.

The proposed approach (FPA β -hc-SVM) is tested using a standard EEG dataset with 64 EEG channels and the data recorded from 109 individuals. In addition, the performance of the proposed method is evaluated using five criteria, which are (i) Accuracy, (ii) F-Score, (iii) Recall, (v) Specificity, and (iv) the number of the channel selected. The FPA β -hc-SVM was tested using two different feature extraction methods, i.e., Wavelet feature *s*(WT) and Auto-regressive models with three different coefficients (i.e., AR₅, AR₁₀, and AR₂₀). The outcomes of the experiments presented the introduced method excelled both standard FPA and the one proposed by [1,2,26–28]. It is worth noting that, while retaining high accuracy rates, the number of sensors has been lessened by half. Additionally, the outcomes displayed a positive correlation between the number of features obtained from the EEG signal and the accuracy ratio. Such a finding suggests that the proposed approach can remove duplicate and undesirable features while retaining specific features.

On the other hand, the current version of the proposed algorithm has some limitations, which are as follows:

1. The proposed algorithm was tested by splitting EEG datasets into three subgroups, i.e., training, validating, and test sets. This approach may lead to overfitting the results. We recommended trying the FPA β -hc-SVM using *k*-fold-cross-validation approach instead.
2. The FPA β -hc-SVM technique was tested using WT features and auto-regressive models only. Future work may recommend testing the proposed method over different features. In addition, we recommend investigating the usage of a multi-objective approach.

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Abbreviations

The following abbreviations are used in this manuscript:

BFPA	Binary Flower Pollination Algorithm
β -hc	β Hill Climbing
EEG	Electroencephalogram
ECoG-BCI	Electrocardiography Brain-Computer Interface
FPA	Flower Pollination Algorithm
RBF	Radial Basis Function
SVM	Support Vector Machines
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
MRI	Magnetic Resonance Imaging
EA	Evolutionary-based Algorithms
TAs	Trajectory-based Algorithms
SI	Swarm Intelligence

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