EEG-based Person Authentication Using Multi-objective Flower Pollination Algorithm

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***Abstract*—Since the past decades, the world has been transformed into a digital society, where every individual is living with a unique identifier. The primary purpose of this id is to distinguish from others and to deal with digital machines which are surrounding the world. Recently, many researchers showed that the brain electrical activity or electroencephalogram (EEG) signals could provide robust and unique features that can be considered as a new biometric authentication technique, given that accurately methods to decompose the signals must also be considered. This paper proposes a novel method for EEG signal denoising based on the multi-objective Flower Pollination Algorithm and the Wavelet Transform (MOFPA-WT) to extract useful features from denoised signals. MOFPA-WT is tested using a standard EEG signal dataset, namely, EEG motor movement/imagery dataset, and its performance is evaluated using three criteria: (i) accuracy, (ii) true acceptance rate, and (iii) false acceptance rate. We show that the proposed method can achieve results that are comparable to the state-of-the-art ones, as well as we draw future directions towards the research area.**

***Index Terms*—EEG, Biometric, Authentication, Flower pollination algorithm, multi-objective**

I. Introduction

Electroencephalogram (EEG) is a graphical recording of brain electrical activity that is recorded from the scalp, and it stands for the voltage fluctuations resulting from ionic current flows within the neurons of the brain [22], [33]. Therefore, EEG signals can provide most of the required information about brain activity, and they are acquired using *invasive* or *non-invasive* techniques [26]. The main difference between these methods is that the invasive approach involves the use of electrode arrays implanted inside the brain, such as *ECoG BCI* for arm movement control [27]. Berger [13] proposed the first use of EEG signals as a non-invasive technique for capturing brain activities. Over the past several decades, researchers have developed Hans's technique to suit versatile applications. For example, EEG signals have been used in medical applications for prevention, diagnosis, rehabilitation, and restoration of patients. The EEG has also been used for non-medical applications, such as education and self-regulation, neuromarketing and advertisement, neuroergonomics and smart environment, games and entertainment, and learning and education, as summarized in [1]. Recently, EEG signals have been successfully used as a new biometric technique in security and authentication applications [1], [21], [22]. The researchers found that EEG signals provide robust and unique features that can be considered as a new biometric technique, being also laborious to be spoofed [26].

Kumar et al. in [22] proposed a user identification system based on EEG signal collected from six users using EMOTIVE EPOC headset with 14 channels. In the preprocessing phase, they used a Butterworth 5th-order filter with a range of 6-35 Hz to achieve the highest signal-to-noise ratio (SNR) of the input EEG signal. In the feature extraction phase, Wavelet Transform (WT) is used to extract features of the EEG signal. Also, three basic statistical measurements (i.e., mean, standard deviation, and energy) were extracted from EEG signals. Concerning the classification phase, LVQ-NN was used to recognize the users. Finally, the recognition rate has been calculated over the different scenarios to find the best combination of channels that can provide the accurate classification.

Later, the same authors investigated some cognitive tasks to design an individual identification system [33]. They used standard EEG datasets related to motor/movement and imaginary tasks [32] with one channel only (i. e., Cz) to obtain the input signal. Also, the authors employed WT to decompose the EEG signal into five levels to extract four different features from each sub-band, namely: (i) energy, (ii) logarithm energy, (iii) absolute energy, and (iv) REE energy. A neural network classifier was proposed to classify EEG signals from five users under four different train-test scenarios based on two tasks. The authors found that the highest identification rates can be obtained using the cognitive tasks based on motor imagination when compared with the results based on motor movement.

Zahhad et al. [2] introduced a new method to improve the performance of EEG-based biometric authentication systems using eye-blinking electrooculographic (EOG) signals. Rodrigues et al. [28] used a binary-constrained Flower Pollination Algorithm [35] to learn the best channels that can provide the

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highest recognition rate for person identification based on EEG signals. Their work was tested using standard EEG datasets as well [32], which recognition rates nearly to 87%, while reducing the number of EEG channels to half.

Kumar et al. [23] proposed a novel method for EEG feature generation that applies a canonical correlation analysis for feature fusion and further improving the recognition rate of the identification technique. The proposed method was tested using a standard EEG dataset [19] that has five mental tasks: (i) baseline, (ii) multiplication of two numbers, (iii) geometric figure rotation, (iv) letter composing, and (v) visual counting. Each task was repeated several times for ten seconds and the EEG signals collected from seven subjects. The proposed method used three techniques to extract the features from the input EEG signals: (i) empirical mode decomposition, (ii) information theoretic measure, and (iii) statistical measurement. A linear vector quantization (LVQ) neural network and its extension (LVQ2) have been used for classification purposes on different mental tasks. The performance of the proposed method provided better results compared with a naïve method for feature fusion.

Safont et al. [29] proposed a biometric authentication method using EEG signals that uses three EEG channels to capture self-collected data from 70 subjects. The authors tested the proposed system using six classification methods, achieving an equal error rate as of 2.4, as well as a classification rate as of 93.8%. Jayarathne et al. [18] proposed a novel approach for EEG-based on biometric authentication as well. They suggested using the EEG signal rather than PIN number for authenticating a person when using ATMs.

Although some works make use of meta-heuristic-based optimization techniques in the context of EEG-based identification, we have not observed any work that makes use of multi-objective optimization. Therefore, the main objective of this paper is to propose a multi-objective Flower Pollination Algorithm combined with Wavelet Transform (MOFPA-WT) to decompose the input EEG signal and find the features that can achieve the highest accuracies. MOFPA-WT is designed using two objective functions: ***min(MSE)*** and ***max(SNR)*** to obtain the best combination of WT parameters for EEG signal denoising. The proposed method is implemented according to the weighted-sum approach to combine multi-objectives into a composite one objective function.

In this work, we used the standard *Motor Movement/Imagery dataset*[1] EEG dataset [17], which includes 109 volunteers with EEG signals captured from 64 channels based on different cognitive tasks. The original EEG signals are then decomposed into five levels to extract features from each subband (i.e., high gamma, gamma, alpha, beta, theta, and delta), where four features are considered: energy, logarithm energy, absolute energy, and REE energy [33].

To evaluate the performance of MOFPA-WT, the results are assessed regarding three measurement factors: accuracy, true acceptance rate, and false acceptance rate. The remainder of this paper is organized as follows. Section II describes the basis for WT-based EEG signal denoising. Section III provides background about the Flower Pollination Algorithm and its multi-objective variant. Section IV describes the proposed system, and the results are discussed in Section V. Finally, the conclusion and future works are stated in Section VI.

[1]https://www.physionet.org/physiobank/database/eegmmidb/

II. EEG Signal denoising using Wavelet Transform

The Wavelet Transform is a powerful and widespread tool for time-frequency domain signal representation, and it has successfully applied for signal compression, feature extraction, and selection, among others [6]–[9], [20]. In general, the WT can be classified into two types: discrete wavelet transform (DWT) and continuous wavelet transform (CWT) [31]. Recently, the WT has been extensively used with non-stationary signals, such as ECG and EEG, mainly due to its robust outcomes in removing EEG artifact noises [20].

In this paper, the DWT has been used to decompose the input EEG signal to extract unique features from each EEG sub-band (i.e., high gamma, gamma, alpha, beta, theta, and delta). One of the popular methods for DWT concerns so-called "Donoho's" approach, which extracted coefficients as follows [34]:

$$C(a,b) = \sum_{i=1}^{N} s(i) g_{j,k}(i) \tag{1}$$

where $C(a,b)$ denotes the wavelet dynamic coefficients, $a = 2^{-j}$ and $b = k2^{-j}$, such that $j \in \mathcal{Z}$, $k \in \mathcal{Z}$, and N stands for the length of the signal. Additionally, a stands for the size of the time scale, b denotes the translation, $s(n)$ is the input EEG signal, and $g_{j,k}(n) = 2^{j/2} g(2^j n - k)$ is the DWT.

The task of DWT is to decompose the input signal using different coefficient levels to correct the high frequency of the input signal. The denoising process involves three phases:

- EEG signal ***decomposition***: the original EEG signal is divided into five levels, at each level the EEG signal is decomposed into two parts, namely approximation coefficients (cA), and detail coefficients (cD). The latter step comprises using a high-pass filter over the signal, and cA will be continuously decomposed for next level.
- ***Thresholding***: for each level, a threshold value is defined according to the noise level of the coefficients.
- ***Reconstruction***: the EEG denoised signal is reconstructed using inverse discrete wavelet transform ***iDWT***.

The WT has five parameters with different types (Table I). The efficiency of noise reduction and unique features extraction relies on the selection of the wavelet parameters. The wavelet denoising process has three phases: the first one concerns the ***decomposition*** of the EEG signal using DWT. This phase involves selecting the appropriate mother wavelet function (Φ) to be used in the EEG signal decomposition task. The second wavelet parameter, i.e., the decomposition level (***L***), is also selected in this phase, and it requires some expertize and experience. It should be noted that the selection of appropriate parameters of the Wavelet Transform (which is one of the main goals of this paper) is recently accomplished using optimization techniques, such FPA, β-hill climbing (β-hc), and genetic algorithm (GA) [7], [9].

In the second phase, the ***thresholding*** is applied. The wavelet provides two standard types of thresholding functions (β), namely **hard** and **soft** thresholding [14], [15]. The thresholding type (soft or hard), selection rules (λ), and rescaling methods (ρ) must all be selected as well, and they strongly affect the global denoising performance. The thresholding value is generally defined based on the standard deviation (σ) of the amplitude the signal [16]. The wavelet parameters (i.e., β, λ, and ρ) must be separately applied for each level (i.e., cA and cD) . In the last phase, the denoised EEG signal is reconstructed by ***iDWT***.

TABLE I: Intervals of the WT denoising parameters.

Wavelet denoising parameters	Method (range)
Wavelet function Φ	**Symlet** (sym1..sym45), **Coiflet** (coif1..coif5), **Daubechies** (db1..db45), and **Biorthogonal** (bior1.1.. bior1.5&bior2.2 .. bior2.8& bior3.1..bior3.9).
Thresholding function β	soft or hard
Decomposition level $\boldsymbol{L}$	5
Thresholding selection rule λ	Heursure, Rigsure, Sqtwolog, and Minimax
Rescaling approach ρ	one, sln, and mln

III. Background

This section provides a background concerning the Flower Pollination Algorithm and its multi-objective version.

A. Flower Pollination Algorithm

In a nutshell, meta-heuristic techniques can be classified into evolutionary algorithms [5], [12], swarm intelligence [10], and trajectory-based algorithms [3], [4], [8]. The Flower Pollination Algorithm is inspired by the pollination behavior of the flowering plants. FPA was introduced by Yang in 2012 [35] and successfully applied for many optimization problems [10], [25]. The rules (operators) of FPA are summarized as follows:

- **Rule(1)**: global pollination involves both the biotic and cross-pollination steps, where the pollinators carry the pollen based on Lévy flights.
- **Rule(2)**: local pollination involves abiotic and self-pollination.
- **Rule(3)**: the reproduction probability is proportional to the similarity between any two flowers.
- **Rule(4)**: the switch probability $p \in [0, 1]$ can be controlled between local and global pollination. Due to some external factors (e.g., the wind), the local pollination comprises a significant portion of the overall pollination activities.

The key rules can be summarized in the pseudocode of the FPA implemented in Algorithm 1, where $\epsilon \in \Re$ denotes a small amount of value.

Algorithm 1 Flower Pollination Algorithm pseudo-code

Objective: $min\ f(\mathbf{x})$, $\mathbf{x} \in \Re^d$
Initialize a population of n flowers (pollens) with random solutions.
Find the best solution x^* in the initial population.
Define a switch probability $p \in [0, 1]$.
Calculate all $(f(\mathbf{x}))$ for n solutions.
$t = 0$
while $t \leq$ *MaxGeneration* **do**
    for $i = 1, .., n$ **do**
        $rnd \leftarrow \mathcal{U}(0, 1)$.
        if $rnd \leq p$ **then**
            Draw a d-dimensional step vector $\boldsymbol{\xi}$ which obeys a Leévy distribution.
            Perform global pollination via $\mathbf{x}_i^{t+1}\mathbf{x}_i^t\boldsymbol{\xi} * (g^* - \mathbf{x}_i^t)$.
        else
            Draw from a uniform distribution $\mathcal{U}(0, 1)$.
            Randomly choose j and k among all solutions, such that $j \neq k$.
            Perform local pollination via $\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \epsilon(\mathbf{x}_j^t - \mathbf{x}_k^t)$.
        end if
        Calculate $f(\mathbf{x}'))$.
        if $f(\mathbf{x}') \leq f(\mathbf{x})$ **then**
            $\mathbf{x} \leftarrow \mathbf{x}'$.
        end if
    end for
    Find the current best solution x^* among all $\mathbf{x}_i^t$.
    $t = t + 1$.
end while

B. Multi-objective Optimization

This section describes a brief introduction to multi-objective optimization. In general, such techniques refer to solving any optimization problem using more than one objective function [24], [37]. The multi-objective optimization problem for m objective functions can be formulated as follows:

$$Min\ \mathbf{f}(\mathbf{x}) = \{f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})\}. \tag{2}$$

where n refers to number of objective functions.

The FPA technique has been extended to the multi-objective optimization domain by Yang et al. [36], while the authors adapted multi-objective Flower Pollination Algorithm (MOFPA) for solving engineering optimization problems. MOFPA is implemented according to the weighted-sum approach to combine two objectives into a composite one objective function. MOFPA defines the multi-objective optimization as follows:

$$f = \sum_{k=1}^{M} W_k f_k \tag{3}$$

and

$$\sum_{k=1}^{m} W_k = 1, \qquad W_k > 0, \tag{4}$$

where W_k stand for a non-negative weight. The essential idea of the weighted-sum approach is that these weighting coefficients consider the preferences for the multi-objectives. Given a set of weights, there is a single Pareto front that is going to be generated for each weight.

IV. Proposed Approach

In this section, we introduce the proposed system for EEG-based user authentication. The proposed approach goes through four phases, in which the output of each stage works

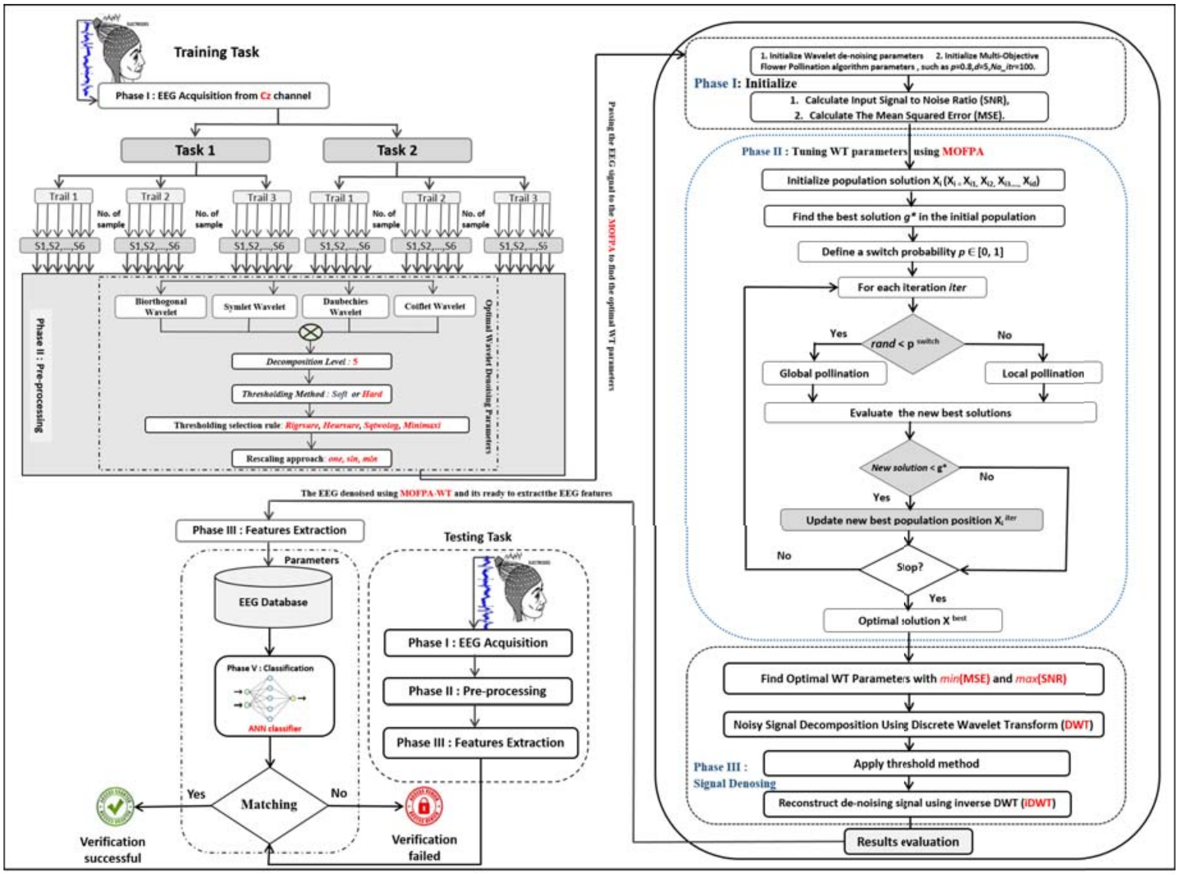

Fig. 1: EEG-based user authentication system proposed in this wok.

as an input to the consecutive one. Figure 1 depicts the proposed approach, which is detailed next.

A. EEG signal acquisition

The EEG signal acquisition is performed over a standard EEG signal dataset [17]. The EEG signals are collected from 109 healthy subjects using a brain-computer interface software called BCI2000 system [32]. The EEG signals are then recorded using 64 electrodes (i.e., channels), and each user performs several motor/imagery tasks that are mainly used in different fields, such as neurological rehabilitation and brain-computer interface applications. In general, these tasks consist of imagining or simulating a given action, such as opening and closing the eyes. The EEG signals are recorded from each volunteer by asking them to perform two tasks according to the position of a target that appears on the screen placed in front of them, as follows:

- **Task 1:** if the target appears on the right or left side of the screen, then the volunteer must open and close his/her fist corresponding to the position of the target on the screen. Then the volunteer relaxes.
- **Task 2:** if the target appears on the right or left side of the screen, then the volunteer imagines open and close his/her fist corresponding to the position of the target on the screen. Then the volunteer relaxes.

In this paper, the input EEG signals are collected only from the cerebral signal (Cz channel) because the cerebral region has a high activity when the user performs any motor-movement task [33]. The acquisition of the input EEG signal is repeated for each user three times, with one minute for interval. Later on, the signal is divided into six samples with $10s$ each.

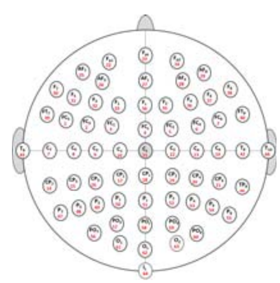

Fig. 2: EEG-based user authentication system proposed in this wok.

B. EEG signal denoising using MOFPA-WT

Despite WT has many advantages and has been successfully used for denoising non-stationary signals such as ECG and EEG [7], [9], most of the current approaches degrade the energy of the original signal when reducing its noise. This situation usually occurs because they consider only the minimum squared error (MSE) between the original and denoised signals. For that reason, this work designs a multi-objective function that considers a balance between reducing the EEG noise and keeping its signal energy.

In this paper, we propose to estimate the optimum/near-optimum set of parameters concerning the Wavelet Transform for EEG signal denoising as a multi-objective optimization task. In our approach, the set of WT parameters is represented as a vector $\mathbf{x} = (x_1, x_2, \ldots, x_d)$ where d is the number of parameters used for the Wavelet Transform[2]. In this context, x_1 represents the value of the mother wavelet function parameter Φ, x_2 stands for the value of the decomposition level parameter L, x_3 refers to the thresholding method β, x_4 represents the value of the thresholding selection rule parameter λ, and x_5 represents the re-scaling approach ρ (the possible ranges for these parameters are described in Table I). Figure 3 depicts the representation of a possible solution using the proposed approach.

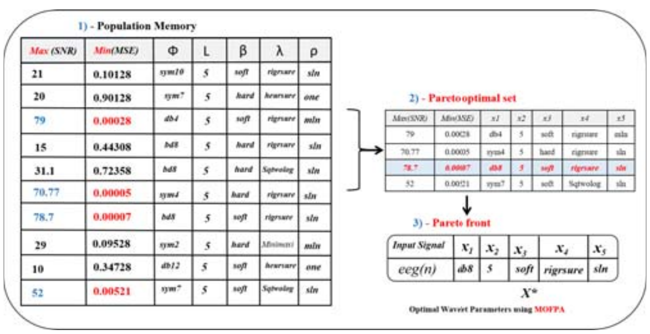

Fig. 3: Modeling the problem of WT configuration for EEG signal denoising using MOFPA-WT.

The proposed MOFPA-WT evaluates each solution using the multi-objective framework applying two objective functions: ***min(MSE)*** and ***max(SNR)***, as formulated below:

$$\begin{aligned}\mathbf{f} &= W_1 f_1 + W_2 f_2 \quad (5)\\ &= W_1 * \mathbf{min}(MSE) + W_2 * \mathbf{max}(SNR), \quad (6)\end{aligned}$$

where the weight vector is initialized as follows:

$$\begin{aligned}W_1 &\sim U(0,1), \quad (7)\\ W_2 &= 1 - W_1.\end{aligned}$$

The two objective functions which are mean squared error (MSE) and signal-to-noise ratio (SNR) are formulated as below:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[x(i) - \widehat{x}(i)]^2 \quad (8)$$

and

$$SNR = 10\log_{10}\left\{\frac{\sum_{i=1}^{N}[x(i)]^2}{\sum_{i=1}^{N}[x(i) - \widehat{x}(i)]^2}\right\}, \quad (9)$$

where $x(i)$ and $\widehat{x}(i)$ denote the original and denoised EEG signals, respectively. Notice that $\widehat{x}(i)$ is obtained using the Wavelet Transform tuned by the proposed MOFPA-WT.

Iteratively, the randomly generated solutions undergo refinement using the MOFPA-WT. The final result of this phase is an optimized solution $\mathbf{x}^* = (x_1^*, x_2^*, \ldots, x_d^*)$ that will be passed to the denoising phase, which involves three main steps that are depicted in Figure 4 and described in more details below:

- EEG signal ***decomposition*** using DWT: in this step, the DWT is applied to decompose the noise of the input EEG signals. In such process, one uses the first two $\mathbf{x}^*$ parameters (i.e., the mother wavelet function and the decomposition level) only. Figure 4 shows the DWT procedure for five levels, where the EEG signal is partitioned at each level into cA and cD components. The latter is processed using a high-pass filter, while the former is processed using a low-pass filter and is decomposed for the next level.
- ***Thresholding***: it is applied based on the noise level of the coefficients. In this step, the last three wavelet parameters, namely, the thresholding type (β), the thresholding selection rules (λ), and the re-scaling methods (ρ), must be selected from $\mathbf{x}^*$.
- ***Reconstruction of the denoised EEG signal by iDWT***: we estimate the value of the original EEG signals by applying *i*DWT on their denoised version. The reconstruction convolves the EEG data using upsampling, which involves the addition of zeros at the even index elements of the signal.

C. Feature Extraction

Extracting effective features plays a significant role in any authentication system [11], [30], [33]. Therefore, the main purpose of this phase is to find unique information from each sub-band (i.e., high gamma, gamma, alpha, beta, theta, and delta) that allow the classification to obtain good results. Figure 4 shows the feature extraction adopted in this work that is based on WT decomposition with five levels. Table II presents the characteristics of the EEG rhythms.

There are several features that can be extracted from the denoised EEG signal. In this paper, we applied four variants of the energy that can be obtained through the sub-bands:

$$feature_1 = EEG_{Energy} = \sum_{j=1}^{M} \mid w_{ij} \mid^2, \quad i = 1,2,3,...,L \quad (10)$$

where M stands for the number of coefficients w_{ij}. The next features are calculated as follows:

$$feature_2 = \frac{Energy\ of\ EEG\ Rhythm}{EEG_{Energy}} * 100, \quad (11)$$

[2]In this paper, $d = 5$.

$$feature_3 = \log(feature_2), \tag{12}$$

and

$$feature_4 = Abs(feature_3). \tag{13}$$

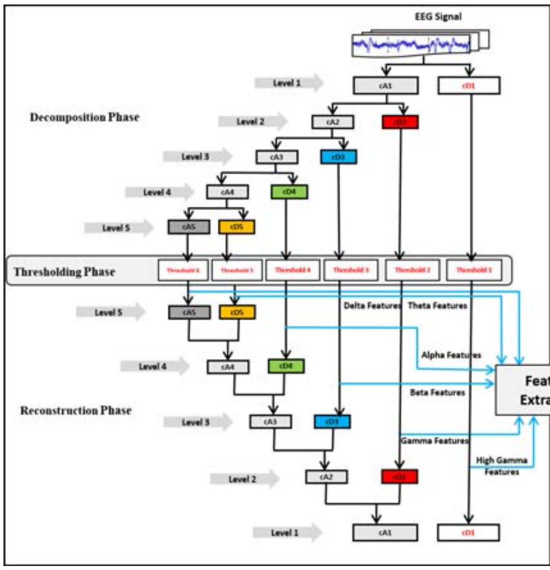

Fig. 4: EEG feature extraction based WT decomposition with five levels.

TABLE II: EEG rhythm main information.

Rhythm	Frequency Range	Frequency bandwidth (Hz)	Decomposition level
Delta(δ)	0-4(Hz)	4	Level 5 (Ac 5)
Theta(θ)	4-8(Hz)	4	Level 5 (Dc 5)
Alpha(α)	8-13(Hz)	5	Level 4 (Dc 4)
Beta(β)	14-30(Hz)	16	Level 3 (Dc 3)
Low Gamma(γ)	30-64(Hz)	34	Level 2 (Dc 2)
High Gamma(γ)	64-128(Hz)	64	Level 1 (Dc 1)

Table III presents the number of features that are used in this work.

D. Neural Network classifier

An artificial neural network (ANN) classifier was applied to classify the extracted features from the denoised EEG signal into correct persons. We designed a network with 24-input features from each subject (i.e., 4 features $*$ 6 sub-bands), 32 hidden layers, and 5 output layers (i.e., the proposed system on evaluated on five users). Notice that such neural architecture was empirically chosen.

V. Results and Discussions

The EEG dataset used in this paper was divided into four different scenarios based on the standard training-and-testing approach for each task. To evaluate the performance of the proposed MOFPA-WT, we considered three measures, namely accuracy, true acceptance rate (TAR), and false acceptance rate (FAR) which can formulated as follows:

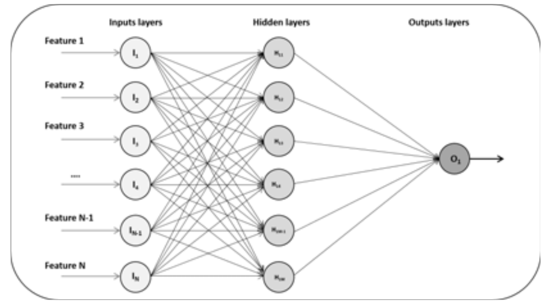

Fig. 5: Multi-layer back propagation ANN adopted in this work.

TABLE IV: Confusion matrix concerning the experiment with 11 persons for training and 7 for testing (task 1).

	Sub1	Sub2	Sub3	Sub4	Sub5	Specificity
Sub1	**7**	0	0	0	0	**0.928**
Sub2	0	**7**	0	0	0	**1**
Sub3	2	0	**5**	0	0	**0.933**
Sub4	0	0	0	**5**	2	**0.9**
Sub5	0	0	0	1	**6**	**0.896**
FAR	0	0	2/7	2/7	1/7	

$$Accuracy = \frac{TA + TR}{TA + FA + TR + FR}, \tag{14}$$

$$Sensitivity(TAR) = \frac{TA}{TA + FR}, \tag{15}$$

$$Specifity(TFR) = \frac{TR}{TR + FR}, \tag{16}$$

and

$$FAR = 1 - TFR, \tag{17}$$

where TA, TR, FA, and FR represent the true acceptance, true reject, false acceptance, and false reject, respectively. The results of the classification phase are represented as a confusion matrix that tabulates whether they fall into one of four categories: TA, TR, FA and FR.

Table IV presents the experiment concerning the training step with 11 persons and testing with 7 individuals (task 1). In this case, we obtained a TAR as of 85.71% and FAR as of 14.28%, which are pretty much interesting and suitable for EEG-based people identification. Table V presents the experiment concerning the training step with 10 persons and testing with 8 individuals (task 1). In this case, we obtained a TAR as of 90% and FAR as of 10%, i.e., we obtained better recognition rates when compared to the previous experiment but using less training cases.

With respect to the task 2, Table VI presents the experiments using 11 individuals for training and 7 for testing purposes. In this case, we obtained a TAR value as of 91.42% and FAR as of 8.58%. Table VII presents the experiments using 10 individuals for training and 8 for testing purposes. In this case, we obtained a TAR value as of 85% and FAR as of 15%.

TABLE III: No. of features of the EEG dataset.

No. of subjects (X)	No. of samples (S)	No. of trails (Tr)	No. of tasks (Ta)	No. sub-band	no. of features	Total No. of features
5	6	3	2	6	4	4320 features

TABLE V: Confusion matrix concerning the experiment with 10 persons for training and 8 for testing (task 1).

	Sub1	Sub2	Sub3	Sub4	Sub5	Specificity
Sub1	**7**	0	1	0	0	**0.968**
Sub2	0	**8**	0	0	0	**1**
Sub3	1	0	**7**	0	0	**0.939**
Sub4	0	0	0	**7**	1	**0.939**
Sub5	0	0	0	1	**7**	**0.939**
FAR	1/8	0	1/8	1/8	1/8	

TABLE VI: Confusion matrix concerning the experiment with 11 persons for training and 7 for testing (task 2).

	Sub1	Sub2	Sub3	Sub4	Sub5	Specificity
Sub1	**7**	0	0	0	0	**0.964**
Sub2	0	**7**	0	0	0	**0.964**
Sub3	1	0	**6**	0	0	**0.965**
Sub4	0	0	0	**6**	1	**0.965**
Sub5	0	1	0	0	**6**	**0.931**
FAR	0	0	1/7	1/7	1/7	

In a nutshell, the best recognition rates were obtained in the task 2 scenario and using 11 individuals for training and 7 for testing purposes. Task 1 obtained better results with less training samples, but the opposite can be observed concerning task 2. However, it is not possible to state whether such assumptions are significant due to the small number of individuals in the dataset. Even nowadays, it is still not straightforward to obtain large datasets for EEG-based person identification. We believe that in the nearby future, small and portable devices for EEE signal acquisition may be available at affordable prices.

Figure 6 shows the accuracy rate considering the input EEG signals based on five decomposition levels using MOFPA-WT. For the sake of visualization purposes, this chart summarizes the experiments conducted in this work. One can observe that the multi-objective paradigm is quite promising to be applied in the context of EEG signal denoising based on the Wavelet Transform. The results obtained are pretty much interesting and they can be extended to larger datasets when they happen to be available. With such a combined framework, we can learn, simultaneously, how to reconstruct and denoise the signal.

TABLE VII: Confusion matrix concerning the experiment with 10 persons for training and 8 for testing (task 2).

	Sub1	Sub2	Sub3	Sub4	Sub5	Specificity
Sub1	**6**	0	2	0	0	**0.968**
Sub2	0	**8**	0	0	0	**1**
Sub3	1	0	**7**	0	0	**0.909**
Sub4	0	0	0	**5**	3	**0.914**
Sub5	0	0	0	0	**8**	**0.906**
FAR	2/8	0	1/8	3/8	0	

VI. Conclusions and Future Work

In this paper, a novel technique for EEG signal denoising based on multi-objective Flower Pollination Algorithm with wavelet transform was proposed. The main task of MOFPA-WT method is to find the efficient decomposition of the input EEG signal which can provide unique features from each sub-bands. MOFPA-WT is tested using a standard EEG signal dataset, namely, EEG motor movement/imagery dataset. The performance of MOFPA-WT is evaluated using three criteria, namely, accuracy, TAR, and FAR. The proposed method achieved the highest accuracies using the cognitive tasks based on motor movement compared with the results based on motor imagination.

Regarding future works, we intend to apply MOFPA-WT in more challenging signal problem instances, such as user authentication or early detection of epilepsy based on EEG signals, as well as to consider MOFPA-WT in larger datasets for EEG-based person identification.

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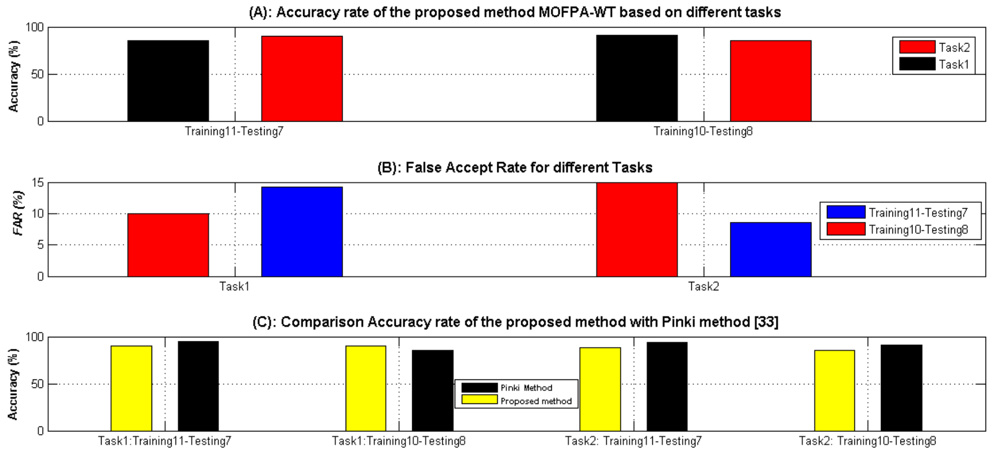

Fig. 6: Accuracy results based on five decomposition levels using MOFPA-WT.

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