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EEG Channel Selection using Differential Evolution Algorithm and Particle Swarm Optimization for Classification of Odorant-Stimulated Records

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ABSTRACT

A significant advancement has been made in the evolutionary computing and swarm intelligence methods in past decades. These methods have been commonly used to calculate well optimized solutions. Methods select the best elements or cases among set of alternatives. In EEG signal processing applications, efficient channel selection algorithms are required to reduce high dimensionality and remove redundant features. To do this, we examined optimal 5 electrodes out of 14 using Particle Swarm Optimization (PSO) and Differential Evolution Algorithm (DEA). The proposed work is related with pleasant-unpleasant EEG odors classification problem. Classification error rates were calculated by Linear Discriminant Analysis (LDA), k-NN (k Nearest Neighbour), Naive Bayes (NB), Regression Tree (RegTree) classifiers and used as fitness function for optimization algorithms. The results showed that PSO with selected 5 channels gave lowest error rates compared with DEA for all runs. RegTree classifier generated optimal fitness function value among other classifiers. PSO algorithm can effectively support channel selection problem to identify the best channels to maximize classification performance.

1. INTRODUCTION

EEG signals have commonly used in many applications such as motor imagery, mental task, and sleep stage classifications in addition to emotion recognition, seizure detection and drug effects diagnosis. EEG records are required multiple electrodes to achieve good performance but some of electrodes may include irrelevant, redundant, and noisy features. Efficient channel selection algorithms are required to remove redundant contents from EEG signals. The purposes of channel selection are reducing computational complexity of any processing task with EEG signals and selecting the relevant channels. [1-2].

Various channel selection algorithms have been proposed in literature. Time domain analysis, wavelet transform, and power spectral estimation can be considered as signal processing tools for feature extraction and channel selection algorithms [2]. Population based search procedures such as Particle Swarm Optimization (PSO) and Differential Evolution Algorithm (DEA) have been in demand for researchers in past decades [3]. These algorithms look for the best subset of channels by individually assessing the usefulness of each channel with the help of search engine and fitness function.

Many numbers of research have been carried out in the area of odor stimulation-based EEG pattern classification and recognition. Schriever et al. (2017) used time-frequency analysis of olfactory-induced EEG in respect to power change. They distinguished olfactory impairment from healthy individuals with sensitivity of 75% and specificity of 89% [4]. Vanarse et al. (2020) demonstrated the classification capabilities of 3D-spiking neural network using Java-based Neucube network by achieving overall accuracy of 94.5% to identify 20 different odor compounds [5]. Kim et al. (2019) investigates EEG activity in response to odors produced by different chemicals. They proved that structure of chemicals, odor types, and sensitivity of olfactory receptors may produce different EEG activity [6]. Aydemir (2017) extracted continuous wavelet transform based features to classify EEG records stimulated from valerian, lotus flower, cheese, and rosewater. He achieved 85.50% classification accuracy using k-NN. He also investigates that gamma EEG sub-band is highly associated with olfaction stimulation [7]. Zhang et al. (2019) presented that channel-frequency convolutional neural network yields best accuracy of 68.79% in gamma band using power spectrum density and differential entropy features using 13 odor stimuli [8]. Laha et al. (2018) evaluated concentration of odors using general type-2 fuzzy set for odor classification. According to their work, higher density of odor yields higher classification performance [9]. Becerra et al. (2018) proposed and odor identification system within 5 sub-bands. of EEG, and

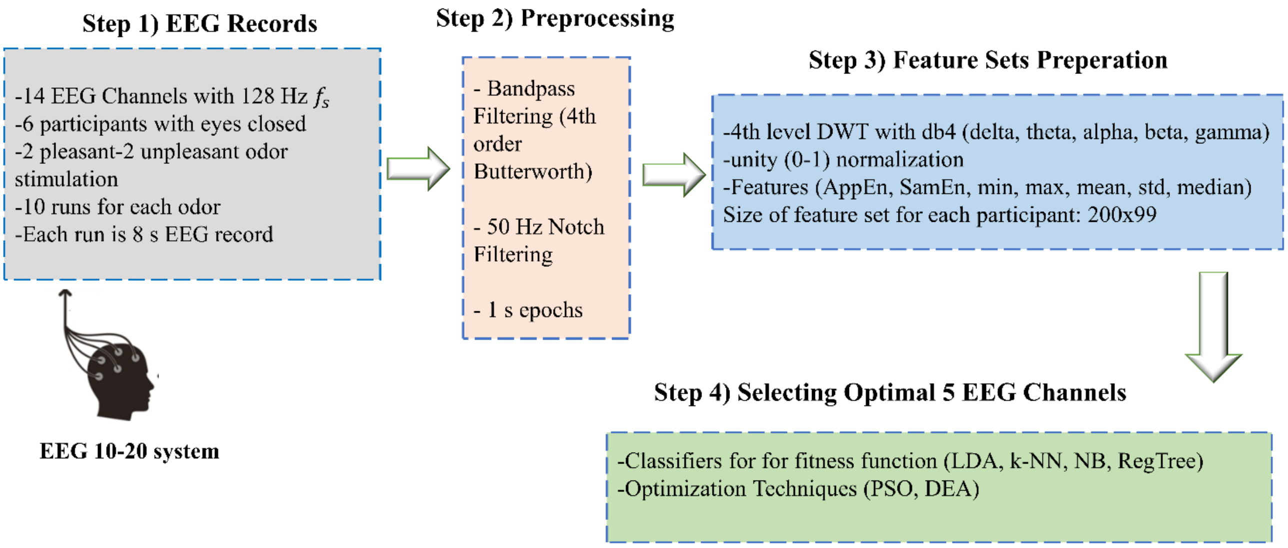

Figure 1. The followed methods in proposed study

statistical features using SVM classifier. They achieved 99.9% classification performance and alpha and beta sub-bands are stated more relevant for odor pleasantness classification task [10]. Zhang et al. (2021) proposed wavelet-spatial domain feature to classify 2 different EEG datasets. They achieved 100% and 94.47% average accuracy for eyes open and closed, respectively using SVM classifier [11]. Finally Hou et al. (2020) used different odors to develop an emotion recognition system based on average frequency band division of EEG signals using SVM. They found 98.9% accuracy for 2 (pleasure and disgust) and 88.5% accuracy for 5 degrees of pleasantness [12].

Some researchers paid attention to apply optimization algorithms to achieve more efficient signal processing system in BCI systems. Li et al. (2020) recommended improved Particle Swarm Optimization (PSO) for feature selection to enhance BCI-based emotion recognition. They achieved 76.67% accuracy for 4-class emotion recognition [13]. Moreover, Qi et al. (2020) showed that channel and feature selection scheme can accelerate the speed of convergence and global optimum and reduce training time in motor imagery based BCI system within PSO [14].

The proposed study stands on the intersection avenue of previous studies. The main purpose of this study to develop a practical EEG channel selection method using population-based methods, namely Particle Swarm Optimization (PSO) and Differential Evolution Algorithm (DEA). We used odorant-stimulated EEG records to classify pleasant and unpleasant odors. We obtained EEG sub-bands and extracted statistical features in line with the previous studies. Error rates obtained from classification algorithms are used for fitness function in optimization problem. We obtained 5 subset of EEG channels that work together perfectly. According to our knowledge, there is no study to carry out similar EEG channel selection task and it strengths the novelty of the paper.

The rest of this paper is organized as follows: Section 2 describes the population-based channel selection methods. Section 3 introduces experimental dataset, preprocessing steps and feature extraction techniques. Section 4 illustrates practical results of PSO and DEA with selected channels. Finally, proposed work is concluded in Section 5.

2. POPULATION-BASED METHODS FOR CHANNEL SELECTION

2.1. Particle Swarm Optimization

PSO was developed by Kennedy and Eberhart (1995) as a meta-heuristic algorithm based on the social behavior exhibited by birds when struggling to reach a destination. The scenario can be assumed as follows: group of birds are randomly looking for food in an area and they don't know where to food is. Effective strategy to find food is following the bird that is known to be nearest to the food [15].

Position and velocity of particles are randomly initialized in search space. Firstly, fitness values of particles are calculated. The best position among all particles is the global best position. The velocity and position of each particle are updated to produce new solutions. Then, the fitness values of the updated particles are recalculated, and best positions are updated.

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Finally, velocities and positions of new particles are generated. When the termination criteria are met, algorithm ends its iterations [15-16].

The velocity of the j_{th} particle (V_j) represented by N dimensional optimization problem 1xN array is as follow:

$$V_j= (V_{j,1}+V_{j,2}+\ldots +V_{j,i}+V_{j,N}) \quad (1)$$

where j= 1, 2, …, M. $V_{j,i}$ is the velocity of the j_{th} particle in the i_{th} dimension calculated as follow:

$$V_j= (V_{j,1}+V_{j,2}+\ldots+V_{j,i}+ V_{j,N}) \quad (2)$$

where j= 1, 2, …,M. $V_{j,i}$ is the velocity of the j_{th} particle in the i_{th} dimension calculated as follow:

$$V_{j,i}^{(new)}=\omega*V_{j,i} + c_1*\text{Rand}*(p_{j,i} - x_{j,i})+c_2*\text{Rand}*(g_i - x_{j,i}) \quad (3)$$

where $V_{j,i}^{(new)}$ is the new velocity, $V_{j,i}$ is previous velocity, ω is inertia weight parameter, Rand is a random value in [0,1], c_1 is cognitive parameter and c_2 is social parameter.
Particles move from old position to new position and this movement is based on the velocities. Particle's position is updated as follows:

$$x'_{j,i}=x_{j,i}+V_{j,i}^{(new)} \quad (4)$$

where $x'_{j,i}$ is new value of ith variable of jth new solution.

2.2. Differential Evolution Algorithm

DEA was developed by Storn and Price (1997). Algorithm was designed mainly for continuous optimization problems. Method compares each trial solution with the best solution previously obtained, and the result of the comparison determines the next trial solution. Population of candidate solutions in algorithm are called agents. These agents are moved in the decision space by using crossover and mutation operators that change their position. If the new position of an agent is an improvement, it is accepted and it replaces the old solutions. This is accepted as success and trial agent is added to population of solutions [15].

In proposed work, the algorithm in [17] was implemented as DEA. This algorithm is simply form of Genetic Algorithm (GA). It looks for the combinational channels that works the best together. For both PSO and DEA, methods are simplest versions of these algorithms.

2. EXPERIMENTAL DATASET, PRE-PROCESSING, AND FEATURE EXTRACTION TECHNIQUES

3.1. EEG Dataset

EEG records are collection of 14 channel, 128 Hz f_s data from 6 male, non-smoker, right-handed undergraduate students between 22-26 ages using the EMOTIV headset while their eyes were closed. Channel labels are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. Related channels can be seen in Table 1. 10-20 international positioning of scalp electrodes is given in Figure 2. 2 pleasant (rosewater, vanilla) and 2 unpleasant (onion-garlic) odors were used in this study. Odors were selected based on other studies [7]. Rosewater and vanilla are expected to include same patterns since both odors give relaxation and pleasantness to subjects, so two odors were taken into one class. Onion and garlic are unpleasant odor substances and allocated for another class. Subjects were asked to breathe normally while sitting on comfortable chair in a ventilated room. The experiment consists of 10 runs. In each run, experimenter was randomly selecting glass tube of odor and kept it under subject's nose for 8 seconds. The reason for choosing short stimuli duration is to prevent unwanted adaptations. The time interval between successive odors is 20 seconds and this break is not included in EEG recordings. After completed 10 trial, same steps were repeated for another odor until 4 odors were used.

TABLE I
CHANNEL NUMBERS AND LABELS

Channel #	Labels
1	AF3 (Left frontmost)
2	F7 (Leftmost frontal)
3	F3 (Left frontal)
4	FC5 (Left frontal-central)
5	T7 (Left temporal)
6	P7 (Left parietal)
7	O1 (Left occipital)
8	O2 (Right occipital)
9	P8 (Right parietal)
10	T8 (Right temporal)
11	FC6 (Right frontal-central)
12	F4 (Right frontal)
13	F8 (Rightmost fontal)
14	AF4 (Right frontmost)

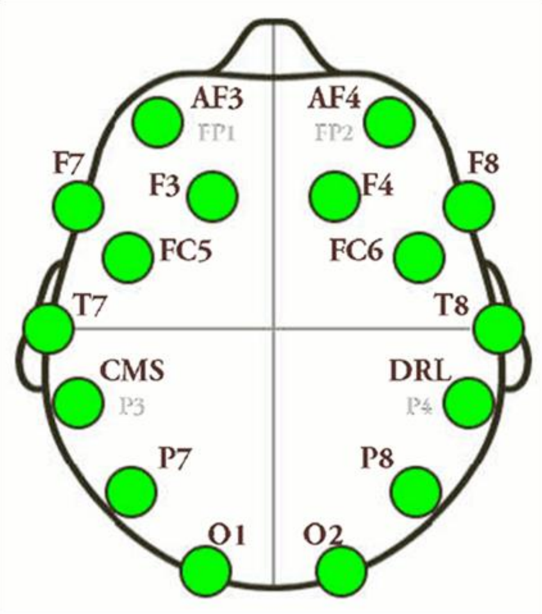

Figure 2. 10-20 International Electrode Positioning of 14 scalp electrodes

3.2. Pre-processing and Feature Extraction techniques

Received EEG records have 0.2-45 Hz signal bandwidth and 50 Hz notch filtered. 3rd order Butterworth band-pass filter was applied to EEG records to extract 0.5-42 Hz band frequency. 8s EEG records were divided into 1 second epochs. Discrete Wavelet Transform (DWT) with db4 was implemented to each epochs using 4th decomposition levels. DWT coefficients were averaged for 8 epochs. 10 trials were combined for each odor. Delta (0.5-4Hz), theta (4-8 Hz), alpha (8-14 Hz)- beta (14-30 Hz) and gamma (30-100 Hz) EEG sub-bands were obtained. Before feature extraction step, data was normalized between 0-1. Normalization method was processed as follows:

$$z_i= (x_i - \min(x))/(\max(x) - \min(x)) \quad (5)$$

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where $x = (x_1, \dots\dots, x_n)$ and z_i is i^{th} normalized data. 7 statistical feature extraction methods were used to reduce the dimension of EEG sub-bands to a smaller set of features. The present features are Approximate and Sample Entropy, minimum and maximum of absolute values, mean value, standard deviation and median.

Besides general known statistical features, Approximate and Sample Entropy need to be explained. Approximate Entropy *(ApEn)* quantifies regularity in short, noisy neural time series by pattern length (m) and similarity coefficient (r). *ApEn* is defined by

$$ApEn = \ln\left(\frac{C_m(r)}{C_{m+1}(r)}\right) \quad (6)$$

in which $C_m(r)$ refers to pattern mean of length m. *ApEn* depends on pattern length. Sample Entropy *(SamEn)* also gives the regularity of signal, and it is independent of pattern length. *SamEn* is calculated as:

$$SamEn = -ln\left(\frac{A^m(r)}{B^m(r)}\right) \quad (7)$$

where $B^m(r)$ refers to probability of 2 sequences match for m points and $A^m(r)$ does for m+1 points. In this work, m is chosen as 2 and r is chosen as 0.2 times standard deviation of time series [19].

Feature vectors were arranged as illustrated in Figure 3. Each odor has 10 trials, and each trial has 14 active channels. 7 features were extracted from each channel. We totally have size of (10 x (14*7)) = 10 x 98 vectors. This size just belongs to one odor and one sub-band. If we take 4 odors into consideration, overall size reaches 40x98. Labels (0-1) were given to last column of vectors for unpleasant and pleasant classes accordingly. Finally, 200x99 feature matrix for each subject was created within combination of EEG sub-bands. Feature vectors were randomized and the 60% of them was considered as training and the rest was for validation.

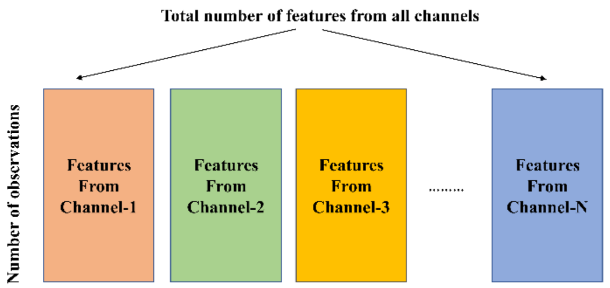

Figure 3. Arranging extracted features in order of channels

3. PRACTICAL RESULTS

Same initial population was defined for both PSO and DEA. Population size was chosen as 100. Number of iterations are limited with 100 and both algorithms stop when iteration number exceeds 100. 5 optimal channels were selected between 14 channels and performance evolution of both optimization algorithms were analyzed. Experiment was repeated for 25 times and classification results were averaged for both algorithms. This study doesn't select optimal number of channels but presents which channel combinations are best for classification. Classification error rates are defined by classifiers and error rates are for fitness functions. In this work, 4 different classifiers were selected which are Linear Discriminant Analysis (LDA) quadratic classifier, k Nearest Neighbor (k-NN) classifier, Naïve Bayes (NB) classifier and Regression Tress (RegTree) classifier. LDA assumes both classes have normal distribution and same covariance matrices. The purpose of LDA is to solve following problem:

$$y = w^T x + w_0 \quad (8)$$

When the distance between two classes maximizes and variance minimizes, the separating hyper plane is obtained and vector of w and w_0 are determined. x refers to feature vector in (7). k-NN uses Euclidean distances with k=3 closest samples. The unlabeled test values are labeled according to closest distance from class samples. NB is a ordinary probabilistic algorithm which uses Bayes' theory. When we consider a group of training trials which includes m discrete features and a class named C, NB can estimate the class of unknown trials using probability to calculate highly probable output. Decision Trees have root of the tree which refers to problem statement and branches of tree which represents set of solutions and consequences. Classification Trees and Regression Trees are types of Decision Trees. Classification Tree is used for categorical target variable and Regression Tree is utilized when Decision Tree has continuous target variable. Root represents population sample, leaves are terminal nodes and child node occurs when nodes are divided into sub-branches. Each step in RegTree can be visualized to help users to make logical decisions. If one criteria is more important than other, RegTree gives priority this criteria and brings it on top of tree. Thus, redundant data is filtered out after each step [20].

4.1. Experiments with PSO

Dimension of the problem equals to number of desired EEG channels. Coefficients c_1 and c_2 were selected as 2. ω was chosen as 0.9 [21]. Optimal 5 channels were determined by the lowest error rates after all runs. Optimal classification error rates for PSO were averaged among 6 subjects and results can be shown in Figure 4. Average optimal error rate in LDA is 11.42%, in k-NN is 5,825, in NB is 12.775 and in RegTree is 0.55% for PSO. Success of selecting optimal sub-channels increases when error rates converge to zero. RegTree classifier gave lowest classification error rate, and it seems to be best algorithm as a fitness function to select optimum 5 EEG channels. NB classifier showed highest classification error rate and it seems to be not a preferable method to select optimum subsets of EEG channels when using PSO.

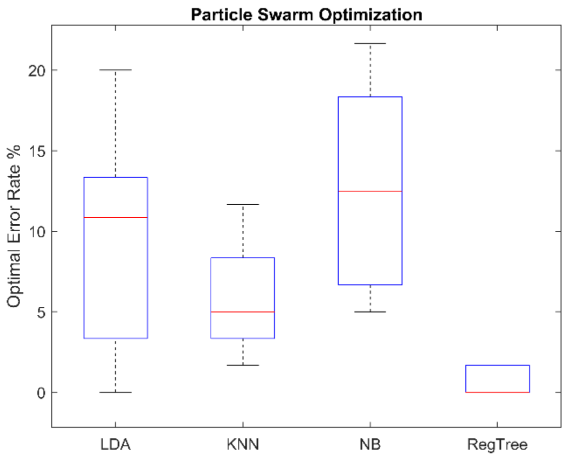

Figure 4. Optimal error rates taken in PSO

4.2. Experiments with DEA

DEA to select optimal subset of channels works as follows: Algorithm selects the first channel, then the second-best channel that works the best with first selected, then the third channel that works the best with the first two selected channels, and these steps continue until selecting last channel. 5 separate channels may perform so weak individually, but when best channels are combined together, they easily outperform. DEA looks for best combination of individual channels. Optimal classification error rates for DEA were averaged among 6 subjects and results can be shown in Figure 5.

Average optimal error rate in LDA is 14.16%, in k-NN is 9.99%, in NB is 18.61 and in RegTree is 4.16 for DEA. RegTree classification algorithm gave also lowest error rate, and it seems to be appropriate algorithm as a fitness function for selecting 5 subsets of channels. The rankings to produce successful fitness values are same as in PSO.

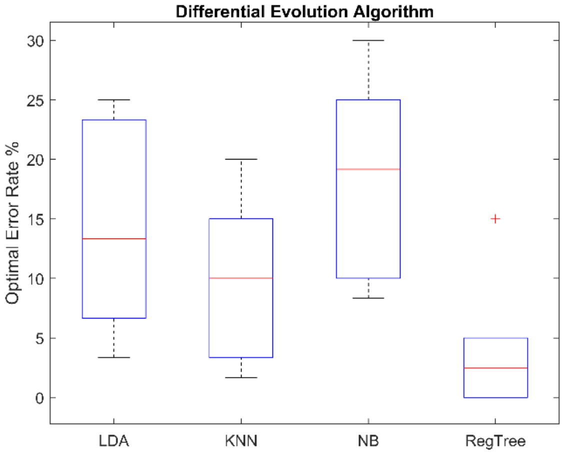

Figure 5. Optimal error rates taken in DEA

In Fig. 4-5, only lowest error rates belong to 6 subjects were taken and averaged. In Fig. 6, average classification results of the selected 5 channels are shown.

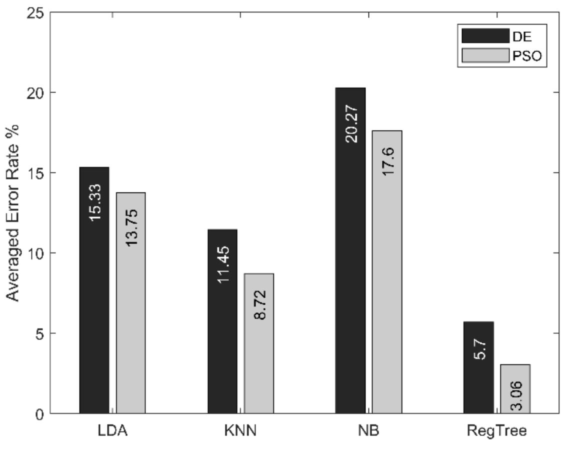

Figure 6. Average error rates of PSO and DEA

Average error rates belong to PSO is nearly 2% lower than DEA. It was noticed that PSO showed better performance than DEA regardless of selected classifiers. Best choice of 5 EEG channel selection is achieved by PSO with RegTree classifier. Selected channels for each subjects using PSO and DEA with RegTree classifier is given in Tab. 2 and 3 respectively.

TABLE II
SELECTED CHANNELS USING PSO WITH REGTREE

Subjects	Optimized Channels	Error Rate(%)
A	AF3 – F7 – T7 – O1 – AF4	1.66
B	F7 – T7 – P7 – F8 – AF4	0
C	F3 – FC5 – T7 – P7 – F8	0
D	F3 – O1 – O2 – P8 – F4	1.66
E	FC5 – T7 – P7 – FC6 – AF4	0
F	F7 – P7 – O1 – FC6 – AF4	0

TABLE III
SELECTED CHANNELS USING DEA WITH REGTREE

Subjects	Optimized Channels	Error Rate(%)
A	AF3-FC5-T7-O1-F8	3.33
B	F3-T7-P7-O1-T8	0
C	F7-F3-P7-O2-F8	15
D	F7-O2-P8-T8-FC6	5
E	F3-T7-P8-FC6-F8	1.66
F	P7-O1-O2-F4-F8	0

The combinations of channels differ from each other for both PSO and DEA even in each iteration, so specific brain regions that are more sensitive with odors cannot be deduced. Table II-III only gives combinations of 5 superior EEG channels that have lowest fitness function values and highest classification accuracies. High error rate gained from subject C using DEA was improved applying PSO.

4. SUMMARY AND FUTURE WORK

In the present study, pleasant and unpleasant odors were applied to 6 subjects to record EEG signals. Filtering process was implemented using band pass filter. DWT was applied to 1 s epochs of signals and wavelet coefficients were calculated. EEG sub-bands were gained using these coefficients. Sub-bands were normalized in range of 0-1. 7 statistical features were extracted to decrease feature space. All EEG sub-bands were combined and totally 200x99 feature matrix were gained. %60 of this features were used for training and rest were for validation.

Population based PSO and DEA optimization techniques were used to select optimal 5 EEG channels and performance of these methods were evaluated. LDA, KNN, NB and RegTree classifiers defined classification error rates to estimate fitness function values. RegTree gave minimum error rates for both PSO and DEA. NB failed to give minimum error rates among other classifiers, but results obtained from NB were still satisfactory. PSO showed better performance than DEA for EEG channel selection in all cases. In current work, 5 optimal out of 14 channels are selected to classify pleasant and unpleasant odor EEG records. The EEG electrode settlement including a greater number of EEG channel may be more convenient to investigate brain regions sensitively. We may also analyze not only 5 but more optimal channels for another study. Selecting different classifiers may be another goal to decrease the classification error rate converging to zero. Including more participants from different gender can strength the generalization of proposed method. In the future work, more population-based algorithms with different fitness function methods may be applied to odor EEG records. Statistical features can be evolved to get higher accuracies. In this sense, selection of EEG subset channels might be in more optimized form.

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BIOGRAPHIES

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