Olfaction Recognition by EEG Analysis Using Wavelet Transform Features

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***Abstract*—The responses of the brain into different information coming from sense organs could be analyzed by various kinds of measuring techniques. Among the existing techniques, Electroencephalography (EEG) is widely used because of its low setup costs, easy implementation and noninvasive nature. The response of the human brain to olfaction has been analyzed in recent years. Particularly, it has not been exactly proved how the human brain gives response to different odors because of the limited kind of odor usage and different kinds of proposed methods. The present study demonstrates the effect of lotus flower and cheese odors on EEG signals, which were recorded from 5 healthy subjects at the eyes open and eyes closed conditions. In order to show the effectiveness of the proposed method, we categorized the EEG trials into two classes between lotus flower and cheese odors. In order to represent the EEG trials, we extracted features by using Wavelet Transform coefficients. As wavelet function, we tested five kinds of wavelets including Morlet, Mexican, Meyer, Coiflet and Daubechies on delta, theta, alpha, beta, whole band of the EEG signal. The extracted features were classified by k-nearest neighbor algorithm. The achieved results showed that among the tested wavelet functions, Mexican wavelet has a great potential to represent the EEG signals which were recorded during smelling of lotus flower and cheese odors under the eyes open and eyes closed conditions. Moreover, we achieved with Mexican 98.29% and 94.08% average classification accuracy rates on the eyes open and closed conditions, respectively.**

Keywords*—electroencephalogram; brain response; olfaction; lotus flower odor, cheese odor; classification; Wavelet Transform; feature extraction

I. INTRODUCTION

Brain is a complex organ which provides balance and is the decision maker mechanism of the human body. All our activities in daily life are controlled by the brain. These controls are carried out by millions of nerve cells (neurons) that communicate with each other in the brain. Electrical activity of these groups of nerve cell in the brain creates electroencephalography (EEG) signals. As the meaning of the term, EEG stands for "brain electrical picture". EEG records are generally taken with the help of a cap surrounding the skull and electrodes placed on the cap. In this regard, EEG is an easy and non-invasive method compared to other imaging techniques [1-3].

Odor molecules in the air move to nose and this event creates olfaction. There are millions of nerve cells that take part in the olfaction in the nose. These cells which stimulate each other via odor molecules taken by inhalation ensure to reach olfaction in the brain [3-5]. Examination of recorded EEG signals during olfaction might clarify that there is any lack or loss of a subject's sense of smell.

Although the response of animal brain in the various kinds of odors was analyzed in detail [6-9], it has not been exactly revealed how the human brain gives response to different odors because of the limited kind of odor usage and different kind of proposed methods.

Melvin et al. analyzed EEG signals which were collected from 14 healthy volunteer human subjects on two levels of scent intensities. In that study they represented the EEG signals with five different features including entropy ratio, entropy difference, entropy mean, root-mean-square and Kurtosis. Instead of classifying the signals, they only showed the feature space in which there is much difference between the features of low intensity and high intensity of scent [10]. In another study by Placidi et al., two kinds of odors, one was pleasant and the other was unpleasant, were smelled by four subjects [11]. Then, the EEG signals were collected when the participants were asked to remember the pleasant and unpleasant odors smelled. Afterwards, they categorized the EEG signals with classification accuracy (CA) rate of between 88.3% and 93.3%. In another kind of odor based EEG works by Kroupi et al., four kinds of odors (including valerian, lotus flower, cheese and rosewater) were smelled by 5 subjects in eyes open and closed conditions [12]. During the experiment, they recorded the EEG signals. Then, they asked the participants the pleasant and unpleasant odors among four of them and they only categorized the EEG signals as the pleasant and unpleasant. They obtained an approximately 90% classification accuracy result on reduced binary classification problem. Moreover, in that study the authors proposed the subject specific categorization model.

In our study, instead of categorization of EEG signals as pleasant and unpleasant, we analyzed the responses of the brain to lotus flower and cheese under the eyes open and closed conditions. To this end, we considered the dataset

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which was served into the public use by Kroupi et. al. In order to represent the EEG signals, we extracted wavelet transform based features. We tested five kinds of wavelet including Morlet, Mexican, Meyer, Coiflet and Daubechies on delta, theta, alpha, beta, whole band of the signal. The extracted features were classified by k-nearest neighbor (k-NN) algorithm which is very easy to implement. The obtained results showed that among the tested wavelets, Mexican wavelet has a great potential to represent the EEG signals recorded during smelling of lotus flower and cheese odor under the eyes open and closed conditions. The proposed wavelet transform based method was successfully applied to the present data and it achieved 98.29% and 94.08% average classification rates under the eyes open and closed conditions, respectively.

II. Materials and Method

A. Data Set Description

In this study, EEG data, recorded in The Swiss Federal Institute of Technology, were used. The EEG signals were presented to the public and were taken from 5 different subjects between aged 26 and 32. These data were obtained by smelling four different odors at subject's eyes open and eyes closed conditions. Data were recorded at 250 Hz sampling rate and 216 electrodes. Although, each trial has duration of 2 seconds, EEG signals were re-referenced to the common average and single trials were generated so as to last for one second after the stimulus onset. Subjects who participated in the experiment do not have any chronic illness, respiratory failure and mental problems. The used odors were as follows: 1- valerian, 2- lotus, 3-cheese, 4- rosewater. In this study, cheese and lotus flower odors were considered to be analyzed. Half of data set are constituted by training data set and rest of them are constituted by testing data set. This selection is carried out in a random form. In this work, data set for odors of lotus flower and cheese is listed in Table 1 with the number of their training and testing trials. Furthermore, in this table *Tr* and *Te* are the numbers of training and testing trials, respectively.

TABLE I. The Number of EEG Trials

Subject	Eyes Open		Eyes Closed	
	Lotus Flower	*Cheese*	*Lotus Flower*	*Cheese*
Subject 1	18 (Tr:9 Te:9)	19 (Tr:10 Te:9)	18 (Tr:9 Te:9)	21 (Tr:11 Te:10)
Subject 2	18 (Tr:9 Te:9)	19 (Tr:10 Te:9)	21 (Tr:10 Te:11)	19 (Tr:10 Te:9)
Subject 3	23 (Tr:12 Te:11)	22 (Tr:11 Te:11)	20 (Tr:10 Te:10)	18 (Tr:9 Te:9)
Subject 4	24 (Tr:12 Te:12)	26 (Tr:13 Te:13)	21 (Tr:11 Te:10)	21 (Tr:11 Te:10)
Subject 5	19 (Tr:10 Te:9)	15 (Tr:8 Te:7)	20 (Tr:10 Te:10)	22 (Tr:11 Te:11)
Total	102	101	100	101

B. Wavelet Transform based Feature Extraction

Wavelet Transform is widely used for extracting features in pattern recognition applications by analyzing the sub-bands of signals in both time and frequency domain [13-15]. The base function of WT is called "wavelet function", which has mean value of zero and finite wave in time. The shifting in time domain and scaling are the important parameters of a wavelet.

WT protects all time-frequency information. Therefore, it provides better performance for processing of non-stationary real signals compared with other methods. The results of the Continuous Wavelet Transform (CWT) are wavelet coefficients which are calculated by summing over all time of the signal multiplied by scaled, shifted versions of the wavelet function (ψ). The CWT of a $Y(t)$ signal is calculated as given in Equation 1.

$$CWT(x,y) = x^{-1/2} \int_{-\infty}^{+\infty} Y(t)\psi\left(\frac{t-x}{y}\right) dt \quad (1)$$

Here, $\psi(t)$, x and y indicate the wavelet function, scaling parameter and shifting parameter, respectively.

In this study, we tested various kinds of wavelet functions including Morlet, Mexican, Meyer, Coiflet for the Delta (D), Theta (T), Alpha (A), Beta (B) and whole band (WB) of the EEG signals. The interval of the bands are given in Table 2. In this table f_L and f_U indicate low cutoff frequency and upper cutoff frequency, respectively.

TABLE II. Frequencies of The Bands

Band									
Delta		**Theta**		**Alpha**		**Beta**		**Whole**	
f_L	f_U	f_L	f_U	f_L	f_U	f_L	f_U	f_L	f_U
0.5 Hz	4 Hz	4 Hz	8 Hz	8 Hz	12 Hz	12 Hz	30 Hz	0.5 Hz	30 Hz

In this study, the features were extracted from CWT coefficients (CWTCs) by calculating their values of mean and standard deviation as given in Equation 2 and Equation 3, respectively.

$$CWTCs^{avr} = \frac{\sum|CWTCs|}{d_{CWTCs}} \quad (2)$$

$$CWTCs^{std} = \sqrt{\frac{\sum(|CWTCs| - CWTCs^{avr})^2}{d_{CWTCs}}} \quad (3)$$

Here d_{CWTCs} denotes the length of the CWTCs. It is worthwhile mentioning that all 216 electrodes were considered for extracting features.

C. Classification and Training Procedure

In this paper, *k*-NN algorithm was used as classifier, which determines the class of a test trial by considering the *k* closest neighbor(s). The *k*-NN classifier is easy to implement, powerful for noisy data and it is also getting more powerful with increasing number of training dataset.

Although there are many kinds of distance metrics, we used Euclidean, which is widely used in literature, to measure the distance of the neighbor(s). The equation for the generalized Euclidean distance might be given as follows:

$$d(x_{ak}, x_{bk}) = \sqrt{\sum_{k=1}^{p}(x_{ak} - x_{bk})^2} \quad (4)$$

Where x_{ak} and x_{bk} are the query point and a case from the examples sample, respectively.

One of the important point at k-NN algorithm is determining the optimum value of k. In this work, we used random subsampling validation method on training data set in order to calculate the optimum k parameter. The optimum k parameter was tuned for each experiment separately.

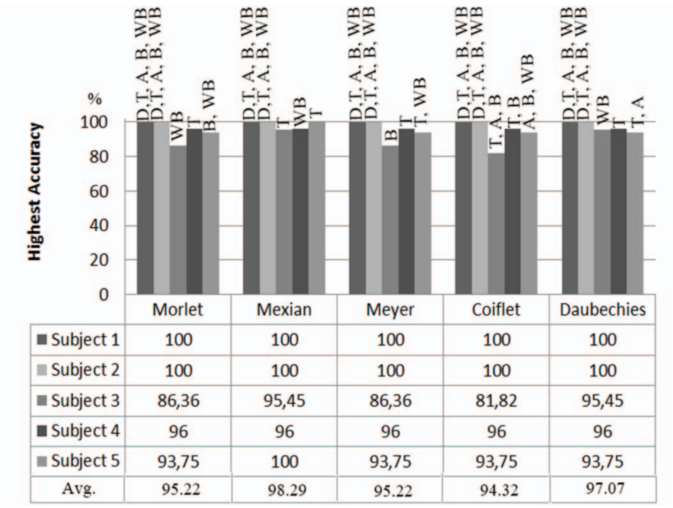
In order to appraise the performance of the k-NN classifier, we calculated CA metric in terms of percentage as follows:

$$CA = \frac{CT}{AT} x100 \quad (5)$$

Where CT indicates the number of correctly classified trials and AT indicates the total number of considered trials.

III. Results

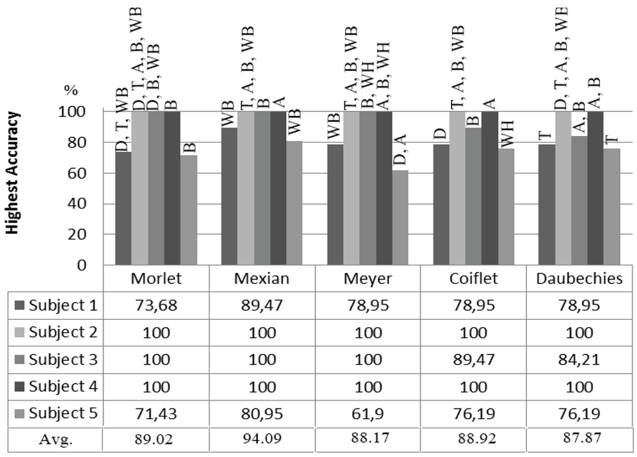
In this work, differences in brain signals of subjects smelling odors of the lotus flower and cheese under eyes open and eyes closed conditions were analyzed. The EEG signals were represented by wavelet transform based on the extracted features. In order to identify the optimal wavelet, Morlet, Mexican, Meyer, Coiflet, Daubechies wavelets were tested. Additionally, delta, theta, alpha, beta, whole bands were analyzed for optimal bandwidth of the EEG signals. Maximum classification accuracy was calculated for these type of wavelets and it was obtained for this type of bands in both eyes open and eyes closed conditions. The obtained results are given in Figure 1 and Figure 2.



	Morlet	Mexian	Meyer	Coiflet	Daubechies
Subject 1	100	100	100	100	100
Subject 2	100	100	100	100	100
Subject 3	86,36	95,45	86,36	81,82	95,45
Subject 4	96	96	96	96	96
Subject 5	93,75	100	93,75	93,75	93,75
Avg.	95.22	98.29	95.22	94.32	97.07

Fig. 1. Eyes open condition of subjects

According to the results obtained from subjects in eyes open condition, the highest CA for olfaction of lotus flower and cheese was calculated at Figure 1. For Subject 1 and Subject 2, 100.00% CA was achieved with Morlet, Mexican, Meyer, Coiflet and Daubechies wavelets on delta, theta, alpha, beta, and whole bands. Furthermore, for Subject 5, 100.00% CA was calculated with Mexican wavelet on theta band. Additionally, for Subject 3, 81.82% CA was obtained with Coiflet wavelet on theta, alpha, beta bands. As shown in the last row of the Figure 1, the highest average of CA in regard to all subjects was obtained as 98.29% with Mexican wavelet.



	Morlet	Mexian	Meyer	Coiflet	Daubechies
Subject 1	73,68	89,47	78,95	78,95	78,95
Subject 2	100	100	100	100	100
Subject 3	100	100	100	89,47	84,21
Subject 4	100	100	100	100	100
Subject 5	71,43	80,95	61,9	76,19	76,19
Avg.	89.02	94.09	88.17	88.92	87.87

Fig. 2.Eyes closed condition of subjects

According to the results obtained from subjects in eyes closed condition, the highest accuracy for olfaction of lotus flower and cheese was calculated at Figure 2. For Subject 2, 100.00% accuracy was achieved with Morlet and Daubechies wavelets on delta, theta, alpha, beta, whole bands and also same CA was obtained with Mexican, Meyer, Coiflet wavelets on theta, alpha, beta, whole bands. Additionally, for Subject 3, 100.00% CA was obtained with Morlet wavelet on delta, beta, whole bands, with Mexican wavelet on beta band, with Meyer wavelet on beta and whole bands. Furthermore, for Subject 4, 100.00% CA was calculated with Morlet wavelet on beta bands, with Mexican and Coiflet wavelets on alpha bands, with Meyer wavelet on alpha, beta, whole bands, with Daubechies wavelet on alpha, beta bands. For Subject 5, 61.90% CA was obtained with Meyer wavelet on delta, alpha bands. As shown in the last row of the Figure 2, the highest average of CA in regard to all subjects was obtained as 94.09% with Mexican wavelet.

Figure 1 and Figure 2 showed that the highest classification accuracies were achieved with Mexican wavelet as 98.29% and 94.09% under eyes open and eyes closed conditions, respectively. Therefore, Mexican wavelet might be put forward as the best wavelet among others. Mexican wavelet was examined for olfaction of lotus flower and cheese on delta, theta, alpha, beta and whole bands in detail. The calculations for considered bands were implemented and the results for the both eyes conditions are given in Table 1 and Table 2.

TABLE III. MEXICAN WAVELET CLASSIFICATION AT EYES OPEN CONDITION OF SUBJECTS

Subject	Delta	Theta	Alpha	Beta	Whole
1	100.00	100.00	100.00	100.00	100.00
2	100.00	100.00	100.00	100.00	100.00
3	72.75	95.45	81.82	77.27	86.36
4	80.00	88.00	80.00	88.00	96.00
5	81.25	100.00	93.75	81.25	93.75
Avg.	86.80	96.69	91.12	89.31	95.22

According to the results obtained from subjects in eyes open condition for Mexican wavelet, the highest CA was achieved as 100% for Subject 1 and Subject 2 on delta, theta, alpha, beta and whole bands, for Subject 5 on theta band. The lowest CA with 72.75% was calculated for Subject 3 on delta band. It might be said that Subject 1 and Subject 2 have more effective sense of smell for olfaction of lotus flower and cheese under eyes open condition than the other examined bands. On the contrary, Subject 3 has a lower sense of smell than the rest of the subjects.

TABLE VI. MEXICAN WAVELET CLASSIFICATION AT EYES CLOSED CONDITION OF SUBJECTS

Subject	Delta	Theta	Alpha	Beta	Whole
1	78.95	68.42	52.63	63.16	89.47
2	94.74	100.00	100.00	100.00	100.00
3	78.95	57.89	78.95	100.00	63.16
4	95.00	95.00	100.00	95.00	95.00
5	47.62	61.90	61.90	71.43	80.95
Avg.	79.05	76.64	78.70	85.91	85.72

According to the results obtained from subjects in eyes closed condition for Mexican wavelet, the highest accuracy was achieved as 100% for Subject 2 on theta, alpha, beta, whole bands, for Subject 3 on beta band and for Subject 4 on alpha band. The lowest CA was calculated as 47.62% for Subject 5 on delta band. It might be said that Subject 2 has more effective sense of smell for olfaction of lotus flower and cheese under eyes closed condition than the rest of the subjects. On the contrary, Subject 5 has a lower sense of smell than the rest of the subjects.

IV. CONLUSION AND DISCUSSION

In this study, EEG trials recorded during smelling of cheese and lotus flower odors were classified based on the features extracted using various types of wavelets on delta, theta, alpha, beta and whole band of the signals. In terms of the average of CA, the Mexican wavelet features provided the highest performances for the both eyes conditions. They were calculated for the eyes open and eyes closed conditions as 98.29% and 94.09% respectively. It is worthwhile to mention that with the usage of Mexican wavelet, the highest CA was calculated on theta band as 96.69% and on beta band as 85.91% under eyes open and eyes closed conditions, respectively. Nevertheless, the lowest CA was calculated on delta band as 86.80% and on theta band as 76.74% under eyes open and eyes closed conditions, respectively.

For the both eyes conditions, 100% of classification accuracy was obtained for three subjects. While previous studies which used the same data set proposed subject-specific feature extraction and classification method, in this study the proposed method can be applied to all subjects in both eyes conditions with higher classification accuracy. Finally, we believe that the proposed study could greatly contribute to the EEG-based olfactory recognition and it could help to quantify olfactory loss for clinical purposes.

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