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Feature Selection with Sequential Forward Selection Algorithm from Emotion Estimation Based on EEG Signals

Talha Burak Alakus*[1], Ibrahim Turkoglu[2]

Abstract

In this study, we conducted EEG-based emotion recognition on arousal-valence emotion model. We collected our own EEG data with mobile EEG device Emotiv Epoc+ 14 channel by applying the visual-aural stimulus. After collection we performed information measurement techniques, statistical methods and time-frequency attribute to obtain key features and created feature space. We wanted to observe the effect of features thus, we performed Sequential Forward Selection algorithm to reduce the feature space and compared the performance of accuracies for both all features and diminished features. In the last part, we applied QSVM (Quadratic Support Vector Machines) to classify the features and contrasted the accuracies. We observed that diminishing the feature space increased our average performance accuracy for arousal-valence dimension from 55% to 65%.

Keywords: emotion estimation, feature selection, support vector machines, EEG

1. INTRODUCTION

Emotion can be described as voluntary or involuntary reactions to external factors like an environment or any stimuli. It plays a crucial role in daily lives and effects all the decisions, moral judgements, prejudices all the time. Basic emotions like anger, fear, happiness reflect the conditions of humans in society and determine their statuses. It is observed that people who reflect positive emotions always are more successful in the community [1].

In order to comprehend the nature and behavior of the emotions, many researchers conduct various studies on emotion analysis with different techniques including physical and non-physical ways. Emotion is an abstract thing thus studies do not reach the desired level. Besides, the mentioned techniques require a high level of data and analysis and as a result of that, data can be very complex and examining the data requires time. Consequently, developing a machine learning and a computer-based system is necessary [2]. Emotions can be collected via various methods such as voice signals, facial expressions, physical activities or body language.

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Although all of these methods are used clearly, it can be manipulated by the subjects with intentionally. This makes interpretation of a raw data wrong and can cause misclassification of emotion data. Hereby, more secure and reliable system is needed thus, the importance of physiological signals -Electrodermal Activity (EDA), Galvanic Skin Response (GSR), Blood Pressure (BP), Electrocardiogram (EKG) and Electroencephalography (EEG) is enhanced [3].

1.1. Electroencephalography

Electroencephalography (EEG) is a way to collect brain signals with electrodes which are placed in the scalp of the brain. Because of advancing technology, EEG signals are not only collected from the hospital but also wearable and portable EEG devices via Wi-Fi and Bluetooth. Figure 1 shows the most popular EEG devices.

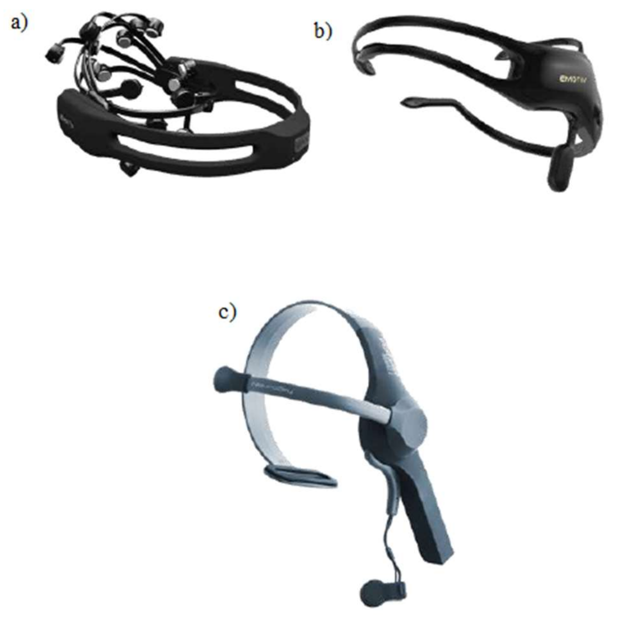

Figure 1. Wearable and portable EEG devices. a) Emotiv Epoc 14 Channel, b) Emotiv Insight 5 Channel, c) NeuroSky Brainwave 1 Channel [4-6]

Brain signals are monitored and conditions of the brain are controlled with brain rhythms. As can be seen in Table 1 there are five brain rhythms that are named based on their frequency and amplitude.

Table 1. Brain rhythms

EEG Rhythms	Frequency (Hz)	Amplitude (µV)
Delta (δ)	1 Hz – 3 Hz	20 µV – 400 µV
Theta (θ)	4 Hz – 7 Hz	5 µV – 100 µV
Alpha (α)	8 Hz – 13 Hz	2 µV – 10 µV
Beta (β)	14 Hz – 30 Hz	1 µV – 5 µV
Gamma (ɣ)	31 Hz – 50 Hz	<2 µV

It is a well-known fact that best brain rhythms for emotion analysis are beta (β) and gamma (ɣ) since their frequency is high and amplitude is low [7]. Electrodes are placed on the scalp with the 10-20 system which is defined by the International Electroencephalography and Clinical Neurophysiology Federation Union standard. Figure 2 represents the 10-20 electrode system.

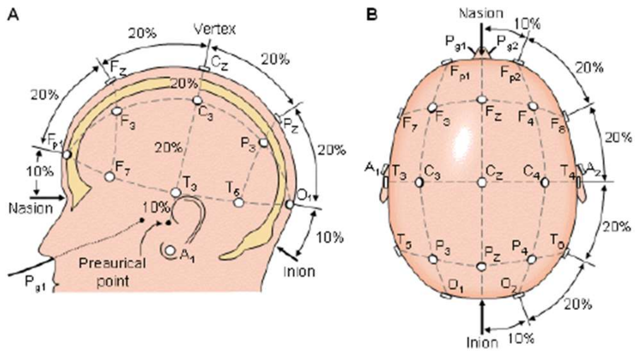

Figure 2. Electrode replacement according to the 10-20 electrode system. a) side of the scalp, b) upside of the scalp [8,9]

Electrodes are disposed on the scalp from nasion to inion and the distances between the electrodes are designated as 10%-20%-20%-20%-10%. The left side of the brain is represented by odd numbers while the right side is represented even numbers. Fp shows the pre-frontal sides of the scalp while F images the frontal parts of the brain. Center side of the brain is specified with ‘C’ and temporal sides are defined with ‘T’. Parietal is the back-side of the brain and specified with ‘P’ whereas occipital part of the brain is defined ‘O’.

1.2. Emotion Models

There are two types of emotion models exist; discrete emotions and dimensional emotions. Discrete feelings consist of positive and negative emotions which include eight basics emotions (anger, anticipation, joy, trust, fear, surprise, sadness and disgust) [10]. On the other hand, the dimensional model includes both arousal-valence and emotion wheel. In the arousal-valence coordinate system, emotions are separated into four different coordinates. The left side of the coordinate plane represents the negative emotions whereas the right side shows the positive ones. Arousal is specified on the axis of the ordinate and emotions are aligned from calm to excited. Yet, valence is represented on the axis of abscissas and emotions are aligned on this axis as positive and negative. In Figure 3, arousal-valence emotion plane is given.

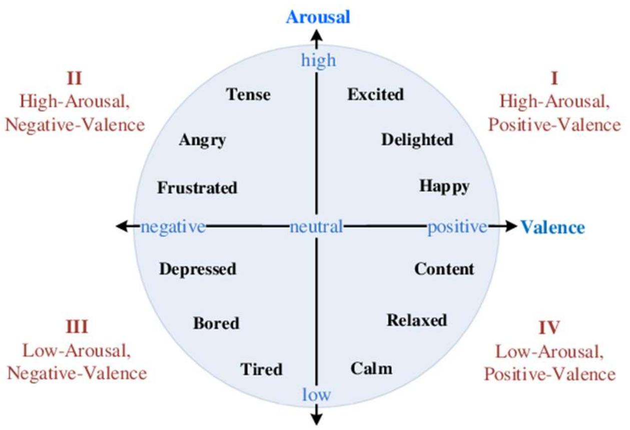

Figure 3. Arousal-valence emotion space [11]

As can be seen in Figure 3 there are four different zones. First two zones are high arousal zones. The first zone includes High Arousal Positive Valence (HAPV) emotions (happy, delighted, excited) and the second zone consists of High Arousal Negative Valence (HANV) emotions (frustrated, angry, tense). Last two zones (3 and 4) are low arousal zones which include Low Arousal Negative Valence (LANV) emotions (depressed, bored, tired) and Low Arousal Positive Valence (LAPV) emotions (content, relaxed, calm). In that model, emotions are not represented by their name but with their arousal-valence coordinate. For example, delighted is not called as delighted but High Arousal Positive Valence (HAPV). Discrete emotions are easier to develop since it classifies and discriminates the specified emotions. However, it is not universal because some of the emotions do not have a definition in some languages [12]. As a result of that, the dimensional model is more common and universal thus many studies applied this model.

1.3. Raw Data Acquisition and Stimulus

In emotion analysis studies, in order to collect raw EEG data and to analyze them some stimuli are used. Stimulus is categorized into three parts; visual, aural and visual-aural.

The visual stimulus includes some images or photographs. The pictures or photographs are shown to the subjects for a certain period of time. During these sessions, EEG signals are collected from subjects. The most popular dataset for visual stimulus is IAPS [13]. Researches can get this dataset by completing the IAPS request form [14].

Aural stimulus consists of sounds or voices. IADS is the well know dataset for aural stimuli [15]. It includes various audio files which are used to stimuli the subjects for a certain period of time. Like IAPS, researchers can obtain this dataset by filling the IADS request form [14].

Visual-aural stimulus contains music clips, short movies, video games etc. which affect the ear and eye at the same time. In the literature, it is observed that DEAP dataset [16] is the most preferred database in studies carried out using both visual-aural stimuli [17]. Like any other databases, researches need to complete the request form and End-User License Agreement [18].

1.4. Evaluation of Stimulus

To evaluate the accuracy of the stimuli, typically SAM (Self-Assessment Manikin) form is used. Generally, in this form, there are four different parameters; valance, arousal, dominance and liking. Subjects rate their feelings according to the parameters after each stimulus session is finished. Each parameter excluding liking has a range of 1 to 9. Figure 4 images a typical SAM form.

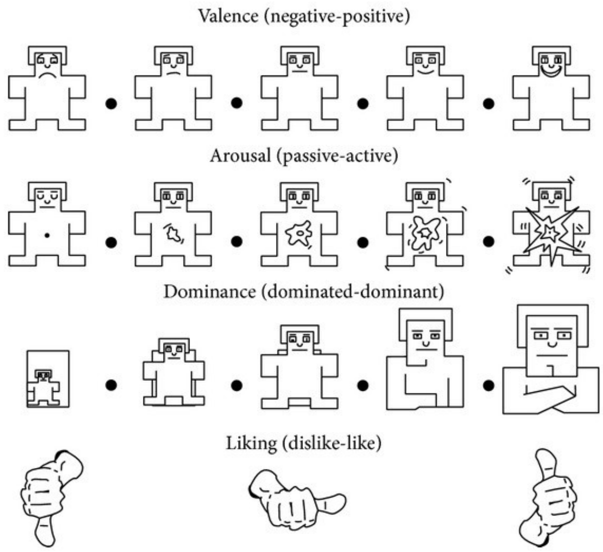

Figure 4. Self-Assessment Manikin [19]

Valence represents the attraction (positive valence) or offensiveness (negative valence) of an event, environment, stimuli or object [20]. In the form, valence is defined from unhappy to happy. If a parameter value is lower than 5 means the subject is unhappy from a given stimulus and represents the low valence. High valence means that the parameter value is higher than 5 and also shows the subject is happy about the stimulus. Considering a parameter value is 5 means that the subject is neutral to the given stimulus.

Arousal is the state of activity against a stimulus. Arousal is identified from calm to excited in SAM. If a parameter value is lower than 5 means the subject is calm from a given stimulus and specifies the low arousal. High arousal refers that the parameter value is higher than 5 and also shows the subject is excited about the stimulus. Considering a parameter value is 5 intends that the subject is neutral to the endowed stimulus.

Dominance shows the submissiveness or prepotency to given stimuli. In the form, dominance is described from obedience to dominance. If a parameter value is lower than 5 means the subject is obedience to a given stimulus and represents the low dominance. High dominance refers that the parameter value is higher than 5 and also shows the subject is dominant to the stimulus. Considering a parameter value is 5 specifies that the subject is neutral to the given stimulus.

The organization of this paper as follows. In Section 2, some studies are explained about EEG based emotion recognition. Their methods, database and classification accuracy also has given. In Section 3, we showed our database, its collection process and technical information about our wearable EEG device. Besides, in this part, feature extraction techniques and feature selection algorithm are mentioned. In the 4th section, we showed the classification accuracy of the EEG channels after the feature selection process. Also, we compared the discrimination accuracy from the original study. In the last section, the study is concluded.

2. RELATED WORKS

In this section, related works about EEG based emotion recognition studies are examined. We observed each study and mentioned their feature extraction methods, classification algorithms, database, and classification performance. According to the literature, the recognition process includes three parts; a) EEG data collection and pre-processing, b) feature extraction and c) feature classification. In some cases, feature selection is also applied to reduce feature matrix into smaller space.

Authors proposed a method based on Kernel Fischer Discrimination Analysis in the study of [21]. They used the IADS database to stimulate 10 different subjects to collect aural stimuli-based EEG data. They applied various feature extraction methods and used the KNN (K Nearest Neighbor) classifier algorithm to discriminate the emotions. They applied dimensional emotion model and classification accuracy is observed 78% from valance plane and 82% from arousal plane.

In the study of [22], researchers used visual-aural stimuli to collect raw EEG data from subjects. They tried to observe and compare the classification accuracy for both 3 electrodes and 8 electrodes system. They applied Higuchi's Fractal Dimension to collect and determine the key features. In order to classify dimensional model emotions, SVM (Support Vector Machines) classification algorithm is used. At the end of the study, they found the average classification accuracy 51,94% and 77,38% for 3 electrodes and 8 electrodes system respectively. The study showed that increasing the number of electrodes makes classification performance high.

Authors in [23] applied Multivariate Synchrosqueezing Transform (MST) to collect key features from EEG signals. By using MST, they removed vibrations from signals then they applied Independent Component Analysis (ICA) to reduce feature vector. In their study, DEAP dataset is handled. For classification ANN (Artificial Neural Networks) is used. At the end of the study, classification performance is observed from arousal 82,11% and from valence 82,03%.

In the study of [24], authors applied Relevance Vector Machines (RVM) to discriminate the positive-negative emotions. DEAP dataset is utilized in that work and for classification. In the feature extraction phase, they applied sample entropy and multi-scale entropy. After this phase, they used both RVM and SVM to classify the emotions. In conclusion, they observed average classification performance with SVM 78,67% and 93,33% with RVM. It showed that RVM is superior from SVM according to the proposed feature extraction methods.

In this study, we performed SVM classifier and different feature extraction methods including statistical analysis, time-frequency domain and chaotic features. They are all generally used for emotion estimation process in the literature yet there are some differences in our study;

- We collected our own EEG data from a portable EEG device by applying our own stimuli. In the literature ordinarily, publicly available datasets or stimuli applied.
- Second, generally datasets obtained from traditional EEG devices. In our study, we performed a wearable and portable EEG device. With this way, we can compare the performance of this device between traditional devices.

3. MATERIAL AND METHODS

3.1. Technical Information About EEG Device

In this study, we used the Emotiv Epoc+ 14 channel EEG device. EEG channels are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. Figure 5 shows the electrode and sensor locations of the device. It has a sequential sampling method and sampling rate can be down sampled both to 128 SPS and 256 SPS. The bandwidth of the device changes from 0.16 Hz to 43 Hz and digital notch filters at 50 Hz and 60 Hz. It has a build in filter which is 5th order Sinc Filter.

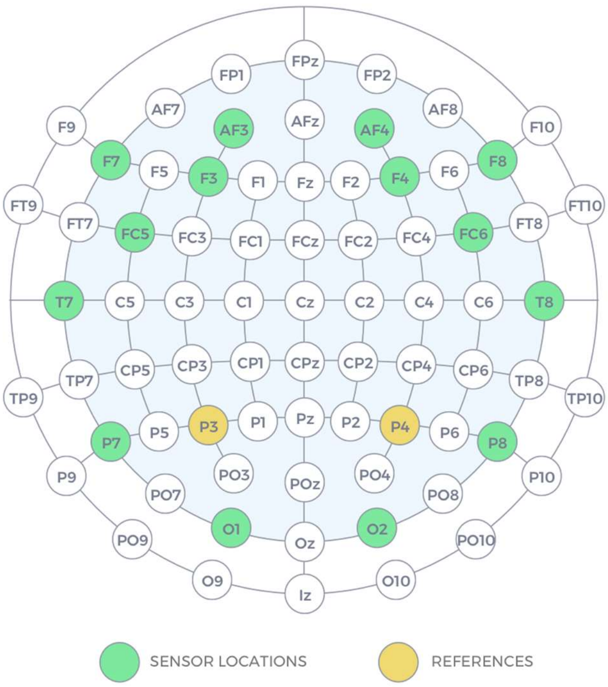

Figure 5. Emotiv Epoc+ sensor and reference locations [4]

In this work, we considered every EEG channel and used the built-in filter to remove artefacts from the device. Also, we configured the sampling rate to 128 SPS.

3.2. EEG Data Collection Process

We collected EEG data from 28 various students from Firat University, Faculty of Technology, Department of Software Engineering. In order to collect the data, we applied 4 different computer games varied from HAPV, HANV, LANV and LAPV. Before data collection, we informed each subject about the study and their usage since participation was voluntary. Later each subject played each computer game for 5 minutes. During that time, we collected EEG signals for every game. After each session, we applied SAM form to analyze the EEG signals. Figure 6 images the proposed data collection process. We collected 20 minutes long data for each subject thus we have 560 minutes long EEG data in our database.

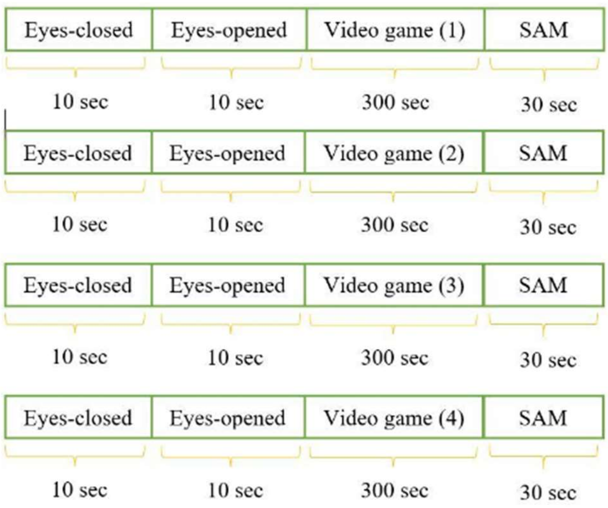

Figure 6. Data collection process

As shown in Figure 6, the first 20 seconds consist of some eye practices. By doing that, we tried to make the subjects focus the games.

3.3. Feature Extraction Methods

Information measurement methods, some statistical techniques and time-frequency domain attributes are used to collect key features. Firstly, we applied Discrete Wavelet Decomposition (DWD) for 4 levels. To do that, we applied the Daubechies wavelet filter with order 2 and collect sub-signals in different frequencies. Later, we applied Detrended Fluctuation Analysis (DFA), Hjorth parameters (H), the average energy of wavelet coefficients (AvgEng), Shannon Entropy (ShanEn), logarithmic energy entropy (LogEn), sample entropy (SampEn), multi-scale entropy (MSCEn), standard deviation (StdDev), variance (V) and zero-crossings (ZC) for each sub-signal. A more detailed description of these methods can be found in [18]. We collected 50 features for each EEG channel. At the end of the feature extraction phase, our feature vector was 50x14x28. The first one indicates the feature number, the second one shows the EEG channels and the last one means the subject numbers. That implies we collected 700 features from one subject and totally 19600 features are available in our database.

3.4. Feature Selection with Sequential Forward Selection Algorithm

Sequential Forward Selection (SFS) is a greedy search algorithm and searches the set from bottom to up. The algorithm starts from an empty set and this set is filled by features selected by some evaluation functions. Here is the pseudo code for the algorithm.

At every rehearsal, the feature is added to the new

1. Starting with an empty set $X_0 = \{\emptyset\}$
2. Algorithm selects the next best feature
   $t^+ = arg_{t \notin X_k} \max J(X_k + t)$
3. Update $X_{k+1} = X_k + t^+; k = k + 1$
4. Go to part 2

dataset which is selected from the remaining features from the feature set. It is selected based on the minimum classification error [25]. It is widely used since it is simple and rapid. Detailed information about this algorithm can be found in [26].

In our study, we used Bayesian Classification (BS) as an evaluation function in SFS algorithm. Besides, in order to validate our results, we performed resubstitution method. After the feature selection process, features are diminished from 50 to 4-9 for each EEG channel. It means that our new feature space was changed from 50x14x28 to [4-9]x14x28. Besides, the number of total features were decreased from 19600 to 1218.

4. CLASSIFICATION ACCURACIES AND COMPARISON

During the study, we applied the QSVM (Quadratic Support Vector Machines) to determine the arousal-valence performance of the EEG signals. We selected the penalty parameter (C) as 1. Besides, we determined kernel scale mode as a gamma. For classification validation, we applied 10-fold cross-validation. After we specified the necessary parameters, we classified the arousal-valence emotion zones. Our multiclass output includes four different classes namely (HAPV, HANV, LANV, LAPV). Table 2 shows the average classification accuracies for each EEG channel with 50 features (before feature selection).

Table 2. Classification of arousal-valence performance before feature selection [18]

EEG	Number of Features	Accuracy
AF3	50	54%
AF4	50	50%
F3	50	40%
F4	50	54%
F7	50	70%
F8	50	63%
FC5	50	34%
FC6	50	34%
O1	50	55%
O2	50	54%
P7	50	66%
P8	50	70%
T7	50	47%
T8	50	79%
Average	50	55%

According to Table 2, the best classification performance observed from EEG channel T8 (79%). This channel also gave the best performance on HANV arousal-valence plane with 96% classification accuracy. Here is the plane classification performance;

- HAPV: Best result is observed from F5 (85%)
- HANV: Best result is collected from T8 (96%)
- LANV: Best result is obtained from T8 (72%)
- LAPV: Best result is achieved from O1 (72%)

After the discrimination process, we eliminated some of the features based on SFS algorithm. We observed that average classification accuracy is increased. Besides all of the EEG channels showed more successful average performance. Table 3 specifies the classification accuracy after feature selection.

Table 3. Classification performance after feature selection

EEG	Number of Features	Accuracy
AF3	4	58%
AF4	4	56%
F3	7	57%
F4	6	65%
F7	6	75%
F8	6	72%
FC5	9	40%
FC6	8	61%
O1	6	68%
O2	8	55%
P7	6	68%
P8	6	73%
T7	4	75%
T8	7	80%
Average	6	65%

Table 3 shows that average classification accuracy 65% which is more successful than the previous average classification accuracy (55%). With the algorithm, we reduced the features for each channel and all of the channels demonstrated better results. Again, T8 EEG channel is the most effective channel with 80% performance. Here is the plane classification performance after feature selection process;

- HAPV: Best result is observed from P7 (93%)
- HANV: Best result is collected from F7 (100%)
- LANV: Best result is obtained from O1 (79%)

- LAPV: Best result is achieved from T7 (93%)

Best performance progress observed from both T7 and FC6 EEG channels. Their accuracy reached 75% and 61% from 47% and 34% with a growth rate of 28 and 27 respectively. In Table 4, the number of selected features for each EEG channel and their names are provided.

Table 4. Selected features with SFS algorithm

EEG	Num. of Features	Feature Names
AF3	4	LogEn (2), ShanEn, and StdDev.
AF4	4	MSCEn, SampEn, ShanEn, and V.
F3	7	DFA, AvgEng, MSCEn, SampEn (2), and ShanEn (2).
F4	6	LogEn (2), SampEn, ShanEn, StdDev, and V.
F7	6	LogEn, MSCEn, ShanEn (2), and V (2).
F8	6	H, LogEn, MSCEn, ShanEn (2), and V.
FC5	9	DFA, H, AvgEng (2), LogEn, MSCEn, ShanEn, StdDev, and ZC.
FC6	8	H, AvgEng, LogEn (3), MSCEn, SampEn, and ShanEn.
O1	6	H (2), AvgEng, SampEn, StdDev, and V.
O2	8	DFA, H (2), AvgEng, MSCEn, SampEn (2), and ZC
P7	6	H, LogEn, MSCEn, StdDev, and V (2).
P8	6	DFA, MSCEn, ShanEn (2), StdDev, and V.
T7	4	LogEn (3), and MSCEn.
T8	7	AvgEng, LogEn (2), MSCEn (2), SampEn, and StdDev.

According to Table 4, some EEG channels have multiple similar features. They are obtained from different wavelet coefficients. For instance, T7 channel has 4 features after the feature selection process, and 3 of them are logarithmic energy entropies and the other one is multiscale entropy.

5. RESULTS

In this study, we performed EEG based emotion recognition with dimensional emotion models. Our study includes four parts; a) EEG data collection, b) Feature extraction, c) Feature selection, d) Feature classification. In EEG data collection phase, we collected our data by applying a visual-aural stimulus from 28 different subjects. We used a wearable EEG device (14 channel Emotiv Epoc+) and 4 different computer games. After collection of EEG signals, we composed our database. It consists of 392 (14(channel)x28(subject)) EEG signals with 20 minutes long. In the feature extraction stage, we performed DWT to transform EEG signals into sub-signals. We utilized Daubechies 2nd order wavelet filter and signals are decomposed into 4 levels. In that way, we collected 4 detailed coefficients and 1 approximate coefficient. After that, we applied some information measurement and statistical methods to obtain key features from each coefficient. 50x14x25 matrix size of features are obtained after this phase. In the third part, we applied the SFS algorithm to reduce the features and disposed of unnecessary features. We evaluated Bayes function to do that and our new vector space reduces for each channel with a different number of features. On average, our vector reduced to 6x14x28 from 50x14x28. On the classification part, we demonstrated QSVM classifier for discrimination of emotions. Firstly, QSVM is used for each EEG channel based on their arousal-valence plane before feature selection. After, we classified the EEG channels based on selected features again and compared their results. We observed that reducing the feature space gives better results and our average accuracy is increased from 55% to 65%.

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