EMOTION RECOGNITION VIA GALVANIC SKIN RESPONSE: COMPARISON OF MACHINE LEARNING ALGORITHMS AND FEATURE EXTRACTION METHODS

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Abstract: *Emotions play a significant and powerful role in everyday life of human beings. Developing algorithms for computers to recognize an emotional expression is widely studied area. In this study, emotion recognition from Galvanic Skin Response signals was performed using time domain, wavelet and Empirical Mode Decomposition based features. Valence and arousal have been categorized and relationship between physiological signals and arousal and valence has been studied using k-Nearest Neighbors, Decision Tree, Random Forest and Support Vector Machine algorithms. We have achieved 81.81% and 89.29% accuracy rate for arousal and valence respectively.*
Keywords: *Biomedical Signal Processing, Emotion Recognition, Pattern Recognition, Machine Learning, Physiological Signal, Galvanic Skin Response, Decision Tree, Random Forest, k-Nearest Neighbors, Support Vector Machine.*

1. Introduction

Emotions play a significant and powerful role in everyday life of human beings. The importance of emotions motivated the researchers in the biomedical engineering, computer and electronics engineering disciplines to develop automatic methods for computers to recognize emotional expressions [1]. For a rich set of applications including human-robot interaction, computer aided tutoring, emotion aware interactive games, neuro marketing, socially intelligent software apps, computers should consider the emotions of their human conversation partners. Speech analytics and facial expressions have been used for emotion detection. Ekman et al. stated that six different facial expressions (fearful, angry, sad, disgust, happy, and surprise) were categorically recognized by humans from distinct cultures using a standardized stimulus set [2]. However, using only speech signals or facial expression signals have disadvantages: using only them is not reliable to detect emotion, especially when people want to conceal their feelings. Compared with facial expression, using physiological signals is a reliable approach to probe the internal cognitive and emotional changes of users.

In this study, emotion recognition from Galvanic Skin Response (GSR) was performed using time domain based features, wavelet approaches and Empirical Mode Decomposition (EMD) approaches. The study compares machine learning algorithms and feature extraction methods for GSR based emotion recognition. Valence and arousal have been categorized and relationship between physiological signals and arousal and valence has been studied using Decision Tree (DT), Random Forest (RF), k-Nearest Neighbors (kNN) and Support Vector Machine (SVM) learning algorithms.

We have achieved 81.81% and 89.29% accuracy rate for arousal and valence respectively by using only Galvanic Skin Response signal. We have also showed that using convolution has positive effect on accuracy rate compared to non-overlapping window based feature extraction.

The outline of the paper is as follows. Section 2 summarizes related work about emotion recognition with GSR. Section 3 describes methods in detail, including emotion representation, data collection, data preprocessing, feature extraction and classification. Results are presented and discussed in Section 4. The paper ends with a conclusion in Section 5.

2. Related Work

Emotions regulate the autonomic nervous system, which, in turn, causes variations in the secretion of sweat on the skin's surface, as well as changes in the heart rate and respiration rate [3].

GSR, which is known also as Electro Dermal Activity (EDA) is a low cost, easily captured physiological signal. GSR is a reflection of physiological reactions that generate excitement. Emotional arousal induces a sweat reaction, which is particularly prevalent at the surface of the hands and fingers and the soles of the feet. When people get excited, body sweats, the amount of salt in the skin increases and the skin’s electrical resistance also increases.

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GSR appears sensitive only to the arousal dimension not direction or valence of the emotion involved. Skin conductivity varies with changes in skin moisture level(sweating) and can reveal changes in sympathetic nervous system. Nakasone et al. have used skin conductance and muscle activity for emotion recognition [4]. Nourbakhsh et al. investigated different time and frequency domain features of GSR in multiple difficulty levels of arithmetic and reading experiments [5]. Channel et al. has conducted a research on emotion assessment related to arousal evaluation using EEG's and peripheral physiological signals. They have used Galvanic Skin Resistance (GSR), blood pressure, temperature as well as EEG data. They have used Naïve Bayes and Fisher Discriminant Analysis (FDA) classifiers [6].

In this study we have used DT, RF, k-NN and SVM learning algorithms using time domain based features, wavelet and EMD approaches.

3. Materials and Methods

Biosensors can monitor physiological attributes of the human body that are controlled directly by autonomic nervous system. These sensors can collect signals including skin conductance, blood volume, temperature, heart rate. Physiological data is challenging to represent and process due to its noise, volume and multimodality. Moreover a persons' emotional response may be different from another.

3.1. Emotion Recognition Using GSR

In this study, we have used Galvanic Skin Response Signals. GSR, which is known also as EDA is a low cost, easily captured physiological signal [4,5,6]. GSR is a reflection of physiological reactions that generate excitement. Skin reacts when it is exposed to emotionally loaded images, videos, events, or other kinds of stimuli, no matter if it is positive or negative. Emotional changes induces a sweat reaction, which is particularly prevalent at the surface of the hands and fingers and the soles of the feet. When people get excited, body sweats, the amount of salt in the skin increases and the skin's electrical resistance also increases. Change in emotions trigger the sweat glands in our body, and make them more active. Whenever sweat glands become more active, they secrete moisture towards the skin surface. That changes the balance of positive and negative ions and affects the electrical currents' flow property on skin and it is most observable on hands and feet. This resistance decreases due to an increase of perspiration, which usually occurs when one is experiencing emotions such as stress or surprise. Resulting changes in skin conductance are measurable and generally termed as Galvanic Skin Response. In GSR method, the electrical conductance of the skin is measured through one or two sensor(s) usually attached to hand or foot.

If the subject's hands are static, like when passively watching a video, then the recommended recording locations are index and middle fingers. In case of the subjects use their both hands, like when using a keyboard and a mouse, then the recommended recording locations are hand palms. However, if the subjects use their both hands, but quite extensively, like when manipulating and interacting with real-life environments, then the recommended recording locations are foot soles. Sensors should be used in inner sides so as not to be affected by the pressure while standing or walking.

In our study, GSR signals have been captured from left hand fingers.

3.2. Emotion Representation

Psychologists proposed and identified different models for representing emotions. There are two significantly different models for representing emotions: the categorical model and the dimensional model. The categorical model and dimensional models have two different methods for estimating the actual emotional states of a person. In the categorical model emotions are labelled. The person is "happy" or "sad" and people get a sense of what is meant. In the dimensional model the representation is based on a set of quantitative measures using multidimensional scaling (e.g. "pleasant-unpleasant") [2,7,8].

The emotion valence-arousal dimensional model, represented in Figure 1, is widely used in many research studies. The Pleasure - Displeasure Scale measures how pleasant an emotion may be. Pleasure(Valence) ranges from unpleasant to pleasant and it is the degree of attraction of a person toward a specific object or event. It ranges from negative to positive. The Arousal-Non Arousal Scale measures the intensity of the emotion. The arousal is a physiological and psychological state of being awake or reactive to stimuli, ranging from passive to active [7,8].

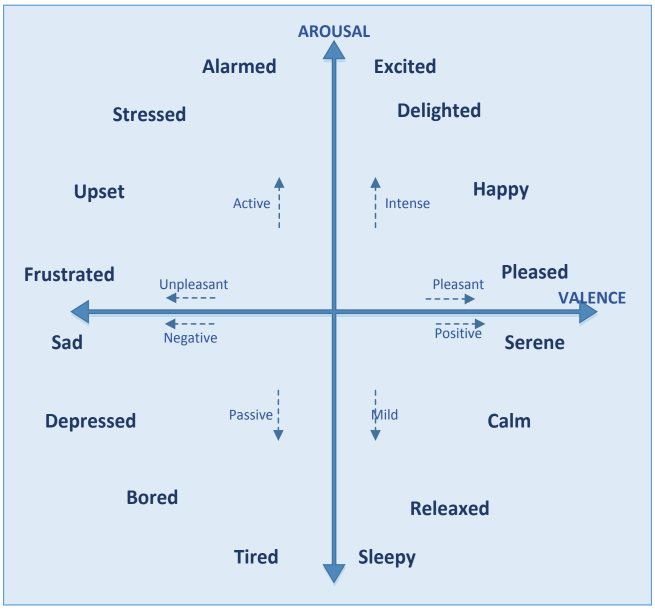

Figure 1. Valence – Arousal Model

Valence-arousal model chart is a model for emotions to be mapped out by range of arousal and valence that is experienced during a particular emotion. The Valence-axis and Arousal-axis separate the coordinate plane into four regions. Let α be the emotional state observed, in valance-arousal plane, a subject can be in one of emotion sets that can be described as follows:

$$\alpha \begin{cases} if\ valence > 0 \wedge arousal > 0,\ \alpha \in \{excited, delighted, happy, pleased, interested, convinced\} \\ if\ valence < 0\ \wedge arousal > 0,\ \alpha \in \{alarmed, stressed, upset, frustrated, insulted, hostile\} \\ if\ valence < 0\ \wedge arousal < 0,\ \alpha \in \{sad, depressed, bored, tired, worried, hesitant, doubtful\} \\ if\ valence > 0 \wedge arousal < 0,\ \alpha \in \{sleepy, relaxed, calm, serene, impressed, peaceful, confident\} \end{cases}$$

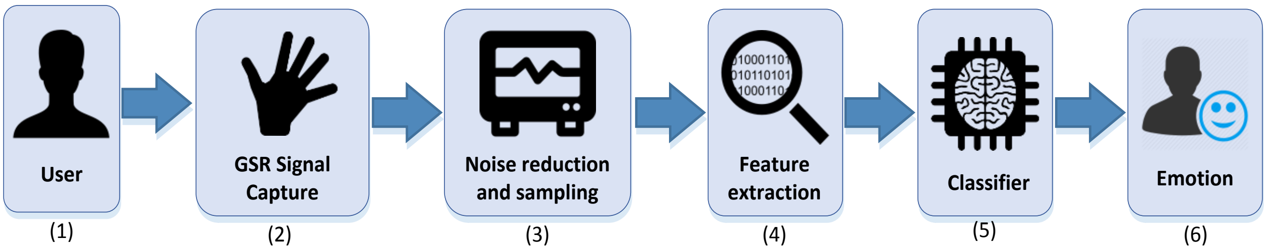

Figure 2. GSR Based Emotion Recognition Pipeline

Table 1. Basic Features and Formulas Used

Attribute	Formula	Attribute	Formula
Minimum	$\min[X_n]$	*Skewness*	$\sum_{n=1}^{N}(X_n - AM)\frac{3}{(N-1)SD^3}$
Maximum	***max[X_n]***	*Kurthosis*	$\sum_{n=1}^{N}(X_n - AM)\frac{4}{(N-1)SD^4}$
Arithmetic Mean (AM)	$\frac{1}{N}\sum_{n=1}^{N} X_n$	*Median*	$\frac{\left(\frac{N}{2}\right)^{th} value + \left(\frac{N}{2}+1\right)^{th} value}{2}$ or $\left(\frac{N+1}{2}\right)^{th}$
Mean Absolute	$\frac{1}{N}\sum_{n=1}^{N}\lvert X_n\rvert$	*Moment (k^{th} order)*	$\frac{1}{N}\sum_{n=1}^{N} X_n{}^k$
Root Mean Square	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}(X_n)^2}$	*First Degree Difference*	$\frac{1}{N-1}\sum_{n=1}^{N}\lvert X_{n+1} - X_n\rvert$
Standard Deviation (SD)	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}(X_n - AM)^2}$	*Second Degree Difference*	$\frac{1}{N-2}\sum_{n=1}^{N}\lvert X_{n+2} - X_n\rvert$

3.3. Emotion Recognition Pipeline

The pipeline we have used in this study is depicted in Figure 2. Galvanic Skin Response signal is captured from subjects through GSR biosensor (1,2). Noise reduction and sampling process is done (3). Feature extraction methods are applied to GSR signal(4), and results represented as feature vectors. Then, feature vectors are fed to classifier. Classifier takes this feature vector as input (5) and makes a prediction about the emotional state of the user (6) by estimating arousal and valence values.

3.4. Dataset

Deap is a multimodal dataset for the analysis of human affective states. In the dataset EEG and peripheral physiological signals of 32 participants were recorded as each watched 40 videos, each video is one-minute long excerpts of music videos. Music video clips are used as the visual stimuli to elicit different emotions.

Participants rated each video in terms of the levels of arousal, valence, like/dislike, dominance and familiarity. For 22 of the 32 participants, frontal face video was also recorded. The dataset was first presented by Kolestra et al. [9]. The data was downsampled to 128Hz, EOG artefacts were removed, a bandpass frequency filter from 4.0 - 45.0Hz was applied and, the data was segmented into 60 second trials and a 3 second pre-trial.

The total signal record time for each video is 63 second and sampling frequency is 128 Hz which means for each channel 8064 sample data points have been collected. The dataset contains both EEG and peripheral physiological signals. In this paper, among recorded signals Galvanic Skin Response signals have been considered. Galvanic skin response signals have been recorded from left hand middle and ring fingers.

3.5. Feature Extraction

Features from signals have been extracted in the time domain and based on statistics. Wavelet and Empirical Mode Decomposition approaches are also used during feature extraction process.

3.5.1. Time Domain Features

GSR signal has been subjected to various length moving windows for feature extraction. In each trial, we have obtained signals and divide each channel signal into segments (e.g. 20 segments with 3s length per segment). Features have been first extracted from each window, and their values across the consecutive windows have been concatenated for each subject and for each video.

In the time domain, arithmetic mean value, maximum value, minimum value, standard deviation, variance, skewness coefficient, kurtosis coefficient, median, number of zero crossings, entropy, mean energy, moments, change in signal values have been considered as features. Table 1 depicts feature list and formula of pertaining features.

In order to capture right attributes for emotion classification, various attributes have been selected as feature set and relationship between arousal and valence has been studied. Table 2 shows studied feature sets and their attributes. FS-10 which includes 10 basic attributes has been used as base set. By enriching FS-10 with different order of moments FS-14 has been obtained. FS-18 contains both FS 14 and for additional attributes. FS-22 is the largest attribute set with 22 features.

Table 2. Feature Sets and Attributes

Feature Set (FS)	Attributes
FS-10	Minimum, Maximum, Arithmetic Mean (AM), Standard Deviation, Variance, Skewness, Kurtosis, Median, Zero Crossings, Mean Energy
FS- 14	Feature 10 Set, $3^{rd,}$ 4^{th}, 5^{th} , 6^{th} Moment
FS- 18	Feature 14 Set, Mean Absolute Value, Max Scatter Difference, Root Mean Square, Mean Absolute Deviation
FS - 22	Feature 18 Set, 1^{st} Degree Difference, 2^{nd} Degree Difference, 1^{st} Degree Diff Divided with Std Deviation, 2^{nd} Degree Diff Divided with Std Deviation

3.5.2. Discrete Wavelet Transformation

Since biological signals are non-stationary and changes over time in nature, Fourier transformation is inconvenient to analyze GSR signals. GSR signals are not periodic and their amplitude, phase and frequencies change. Wavelet transformation is generally can deal with non-stationary signals. Discrete Wavelet Transformation is a method developed to overcome the deficiencies of the Fourier transformation over non-stationary signals and this method is less sensitive towards noise and can be easily applied to non-stationary signals [10]. Features have been extracted using Discrete Wavelet Transform. For the DWT, it is important to identify appropriate wavelet type and determining the level of decomposition. Daubechies db2 has been selected as wavelet.

The features are the sum of absolute amplitudes, min, max, mean energy, sum of squares, kurtosis, skewness, and standard deviation.

3.5.3. Empirical Mode Decomposition

In this study, we proposed and evaluated the use of Empirical Mode Decomposition (EMD) technique. The

GSR signal data were separated into intrinsic mode functions (IMFs) using the EMD method. EMD is the fundamental part of the Hilbert-Huang transform (HHT) which is a way to decompose a signal into so-called intrinsic mode functions (IMF) along with a trend, and obtain instantaneous frequency data [11, 12]. Empirical mode decomposition (EMD) and the Hilbert spectral analysis (HSA) are used together in HHT and act as a signal transform method. But EMD can be used separately as a signal feature extraction method, too. It is used in a variety of studies such as decomposition of speech signal [13], epileptic seizure detection in EEG signals [14], extraction of significant features [15] etc.

The algorithm itself depends on enveloping the signal functions maxima and minima, finding the mean, extracting an IMF and iterate this steps until the peak frequency becomes smaller than the defect one. In our study we have used EMD for feature extraction. After applying EMD, we have extracted Minimum, Maximum, Average, Standard Deviation, Variance, Skewness, Kurtosis, Median, Zero Crossings, Mean Energy, 3rd Moment, 4th Moment, 5th Moment and 6th Moment as features.

3.6. Classification

Labeling the samples is critical for Machine Learning. Arousal and Valence values have been categorized to two (Low, High) classes. We divide the trials into classes according to each trial’s rating value (high: ≥ 4.5, low: < 4.5). GSR signals taken from 32 subjects all have been used for training and test steps. After feature extraction the signals are classified into classes using classifiers Decision Tree(J48), Random Forest, Support Vector Machine (SVM) and k-Nearest Neighbors(kNN).

A decision tree is a non-parametric supervised learning method that predicts the value of a target variable by learning decision rules from the data and used for classification and regression. Decision tree partitions dataset into groups as homogeneous as possible in terms of the variable to be predicted. Attribute selection is the fundamental step to construct a decision tree. Entropy and Information Gain is used to process attribute selection. ID3 and C4.5(aka J48) algorithms have been introduced by J.R Quinlan which produce reasonable decision trees. C4.5 is an extension of ID3 algorithm [16].

Random Forests are an ensemble method with which classification and regression are performed using a forest of decision trees, each constructed using a random subset of the features. Random forests achieve high accuracy in a variety of problems, making them versatile choice for many applications. Since only a subset of the features used, random forests capable of handling high dimensional data. Also, a trained model can be used to determine the pairwise proximity between samples. These features make random forests a popular technique in bioinformatics and specialized random forests for these purposes are an active area of research [17].

The support vector machine (SVM) is a supervised method that constructs a hyperplane separating groups based on a set of given training data in a multidimensional space. Objective of the SVM is to find the optimal separating hyperplane which maximizes the margin of the training data. SVM supports both regression and classification tasks. SVMs can perform linear classification tasks. SVMs can also perform a non-linear classification using what is called the kernel trick, by mapping their inputs implicitly into high-dimensional feature spaces. SVMs produce robust, accurate predictions, and are least affected by noisy data, and are less prone to overfitting [18].

k-Nearest Neighbors algorithm (kNN) is a nonparametric method used for classification and regression [19]. C4.5 builds a decision tree classification model during training. SVM builds a hyperplane classification model during training. kNN does not build such classification model, it just stores the labeled training data. For a new unlabeled instance, it looks at the k - closest labeled training data points and then using the neighbors’ classes and determines class.

4. Experimental Results and Discussion

We have conducted tests with time domain only features, wavelet and EMD approaches. During test process, we have tested all feature sets and compared the results in time and frequency domains. We have used feature sets as part of feature vectors to train and test classifiers. In order to compare classifier performances we have also conducted test cases with Decision Tree(J48), Random Forest, Nearest Neighbors (kNN) classifiers separately.

4.1. Time based Statistical Features Tests

Tests have been conducted with 10-fold cross validation by using Random Forest machine learning algorithm. Window Duration $W \in \{1, 3, 5, 8, 10, 12, 15, 30, 60\}$ s, Feature Set Size $FS \in \{10, 14, 18, 22\}$, and Convolution $C \in$ {Convolution, Non-Convolution} setups have been tested with various combinations.

Window Duration Size Tests

Window duration has effect on accuracy rate. Various window size duration between 1 seconds and 60 seconds have been selected. Tests with 3 seconds window duration performed better than other window duration size. Results are depicted in Table 3 and Figure 3.

Feature Set Tests

Feature extraction has effect on accuracy rate. Various feature sets(FS) have been selected. Tests with FS 10, FS 14, FS 18 and FS 22 has been conducted. FS 14 performed better than other feature sets, corresponding results are depicted in Figure 4.

Convolution vs. Non-Convolution Tests

Windows have been slided by collapse or not collapse manner. Overlapped and one second slide duration has performed better compared to non-overlapping window sliding. Figure 3 and Figure 4 confirms that convolution is generally a better approach to increase accuracy rate.

Table 3. GSR – Time Domain Statistics Experiments

Feature Size	Record Size	Class Size	AROUSAL Accuracy No -Conv	AROUSAL Accuracy Convolution	VALENCE Accuracy No-Conv	VALENCE Accuracy Convolution	Window Duration (sn)
10x63	40x32	2	70.78%	70.78%	69.6%	69.6%	1
10x21	40x32	2	71.53%	71.46%	70.54%	71.04%	3
10x12	40x32	2	70.46%	70.76%	69.68%	70.39%	5
10x8	40x32	2	69.6%	70.17%	69.49%	70.23%	8
10x6	40x32	2	69.0%	70.15%	69.32%	69.76%	10
10x5	40x32	2	68.96%	69.45%	69.21%	69.56%	12
10x4	40x32	2	68.75%	68.9%	68.92%	69.07%	15
10x2	40x32	2	68.04%	68.44%	68.21%	68.37%	30
10x1	40x32	2	66.48%	66.48%	65.7%	65.7%	60

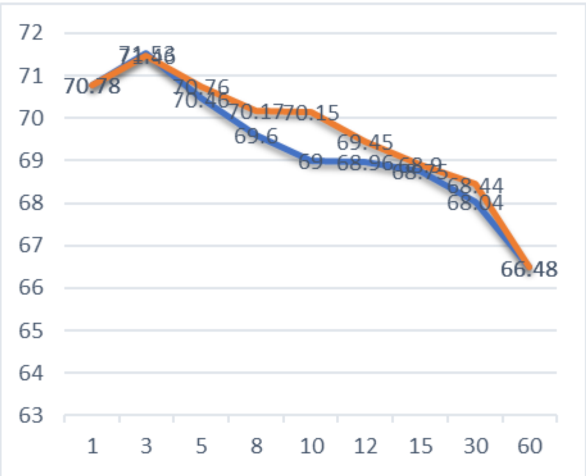

Figure 3. Windows Sizes vs.Accuracy Rate

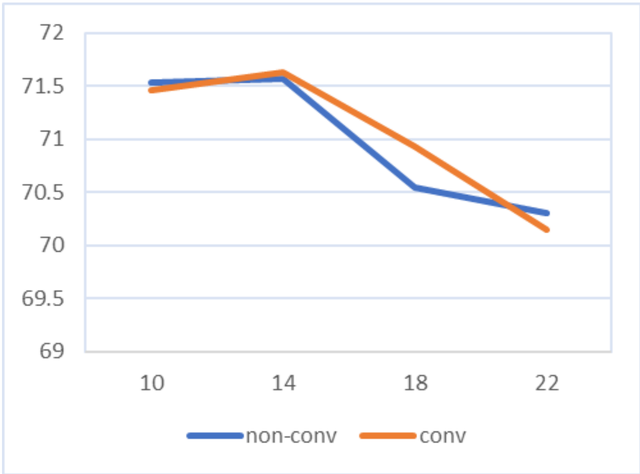

Figure 4. Feature Sets vs. Accuracy Rate

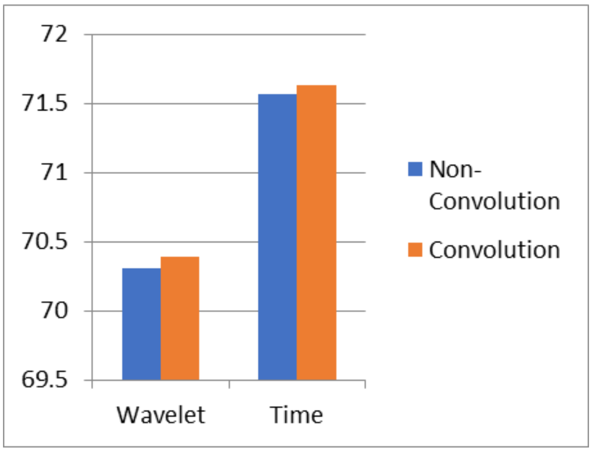

Figure 5. Wavelet and Time based features vs Accuracy

Table 4. Wavelet versusTime Domain Statistics Experiments

Class	**Wavelet**		**Time**	
Arousal	70.31%	70.39%	71.53%	71.46%
Valence	70.7%	70.31%	70.54%	71.04%
	Non-Conv	Conv	**Non-**Conv	Conv

4.2. Wavelet versus Time Based Features Tests

Time based features and wavelet approach have been compared by tests. Time based features performed better as shown in Table 4 and Figure 5.

4.3. Classifier Comparison Tests

Tests have been conducted with 10-fold cross validation by using various classifiers C ∈ {Decision Tree(J48), Random Forest, Nearest Neighbors (kNN)}and Feature Set Size F ∈ {10} and Window Duration W∈ {3} seconds configurations. Table 5 depicts accuracy rates for various Classifiers for arousal and valence respectively.

Table 5. Accuracy Rates for various classifiers

Dimension	kNN	DT	RF	SVM
Arousal	58.12	59.21	71.53	71.40
Valence	60.54	59.20	71.04	70.54

4.4. EMD Features Tests

GSR signals have been tested with Window Duration W ∈ {3} s, Feature Set Size ∈ {FS-14}, since these setups were best with statistical only feature extraction methods. After feature extraction step, all features have been used as input vector to Random Forest classifier. To verify the effectiveness of this method, 32 subjects were tested.

Applying EMD for feature extraction gave better results both for arousal and valence dimensions. EMD performed better compared to time-only statistical feature extraction. The accuracy rate increased from 71.93% to 85.07% for arousal and from 71.04% to 82.81% for valence as depicted in Table 6 respectively.

Table 6. EMD based Results

Dimension	Non – EMD Accuracy %	EMD Based Accuracy %
Arousal	71.53	81.81
Valence	71.04	89.29

5. Conclusion and Future Work

The methods of recognizing arousal and valence values directly from only GSR Signals is a challenge task. In this study, an emotion recognition system based on GSR is introduced by considering affective and physiological computing approaches. Emotion recognition from GSR signals was performed. In this work, Valence and arousal have been categorized and relationship between GSR signals, arousal and valence has been studied using Decision Tree, Random Forest, k-Nearest Neighbor and Support Vector Machine algorithms.

We have seen that there is a relationship between GSR signals, arousal and valence. In case of we categorize both arousal and valence into two classes; we have achieved 71.53% and 71.04% accuracy rate for arousal and valence respectively with time domain only features.

Applying EMD increased accuracy rate both for arousal and valence dimensions. EMD performed better and yielded a modest increase in the performance compared to time-only statistical feature extraction. Based on the results, the accuracy rate increased from 71.93% to 85.07% for arousal and from 71.04% to 82.81% for valence. The results suggest that the proposed EMD based approach is effective for GSR signals, and EMD based feature extraction is worth for the further application in the physiological signal analysis.

For future works, we are planning to apply data fusion techniques with other physiological signals and apply different machine learning algorithms to increase accuracy rate.

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