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Review on Support Vector Machine (SVM) Classifier for Human Emotion Pattern Recognition from EEG Signals

[1]Noor Aishah Atiqah Zulkifli, [1]Sawal Hamid Bin Md. Ali,
[3]Siti Anom Ahmad and [2]Md. Shabiul Islam
[1]Department of Electrical, Electronic and Systems Engineering,
Faculty of Engineering and Built Environment,
[2]Institute of MicroEngineering and Nanoelectrics (IMEN),
National University of Malaysia, 43600 UKM, Bangi Selangor, Darul Ehsan, Malaysia
[3]Department of Electrical and Electronic, Faculty of Engineering, University Putra Malaysia,
43400 UPM Serdang, Selangor Darul Ehsan, Malaysia

Abstract: This study reviewed the strategy in pattern classification for human emotion recognition system based on Support Vector Machine (SVM) classifier on Electroencephalography (EEG) signal. SVM has been widely used as a classifier and has been reported as having minimum error and produce accurate classification. However, the accuracy is influenced by many factors such as the electrode placement, equipment used, preprocessing techniques and selection of feature extraction methods. There are many types of SVM classifier such as SVM via Radial Basis Function (RBF), Linear Support Vector Machine (LSVM) and Multiclass Least Squares Support Vector Machine (MC-LS-SVM). SVM via RBF states the average accuracy rate of 92.73, 85.41, 93.80 and 67.40% using different features extraction method, respectively. The accuracy using LSVM and MC-LS-SVM classifier are 91.04 and 77.15%, respectively. Although, the accuracy rate influenced by many factors in the experimental works, SVM always shows their function as a great classifier. This study will discuss and summarize a few related works of EEG signals in classifying human emotion using SVM classifier.

Key words: Emotion recognition, accuracy rate, Electroencephalography (EEG), artifacts removal, classifier method, Support Vector Machine (SVM)

INTRODUCTION

Classification can be referred as a process or an action of segmentation based on their qualities or characteristics. This process has been widely implemented in many area of research especially in pattern recognition such as classification of movements by EMG, patients with chronic hemiparesis, texture face recognition, Vein Pattern and also human emotion.

Extensive researches and study have been carried out in recent years to investigate the classification system of human emotions. Emotion is one of the most important features of humans in how we experience and interact with each other, the environment and they also affect our decision-making, attention, reasoning and memory (Murugappan *et al.*, 2009). There have been plenty of interests in exploring and developing this field for many applications such as emotion robot, smart sensor, human-robot interaction and automotive driver.

Automotive driver plays an important role inensuring the safety of drivers on the road. Based on Malaysian Institute of Road Safety Research (MIROS) report by Zainal Abidin, the way of a person drives influenced by their emotions stability. The fatalities related to the emotions are high compare to the other factor such as machine defect and environmentwith 284 cases as shown in Table 1. Fatigue, risky driving and speeding are the effect of instability emotions. A person who often in sadness are easier to feel fatigue and drowsiness reported by Yang. Unstable emotions of a driver also lead to the risky driving and speeding.

Corresponding Author: Noor Aishah Atiqah Zulkifli, Department of Electrical, Electronic and Systems Engineering, Faculty of Engineering and Built Environment, National University of Malaysia, 43600 UKM, Bangi Selangor, Darul Ehsan, Malaysia

Table 1: Number of fatality and crash occurrence factors

Factors	No. of fatalities	Total
Instability emotions		
Fatigue	70	284
Risky driving	121	
Speeding	93	
Machine defect		
Brake	20	34
Tyre	14	
Environment		
Road defect	36	70
Roadside hazard	34	

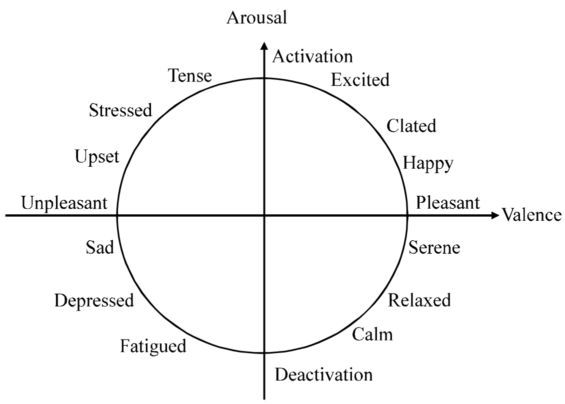

Fig. 1: 2D emotion model by valence-arousal

Human emotion models: Different researchers have different views and findings regarding the emotion. Ekman and Friesen (1986) proposed six universal emotion that have been widely used for human recognition researches. The six emotions are happiness, sadness, anger, fear, disgust and surprise. In 1992, Ekman added a few emotions to the list but stated that not all of these can be encoded via facial expressions: amusement, contempt, contentment, embarrassment, excitement, guilt, proud of, relief, satisfaction, sensory pleasure and shame. Parrot has recorded 138 emotional states which is the highest emotional states recorded.

Simplified framework of emotion model consist of two axis: valence (positive vs. negative) and arousal (high vs. low) (Ekman, 1992) as Fig. 1. All the emotions are classified into this four quadrant according to their group.

In the process of interpreting emotions, psychophysiological signal which is known as bio-signal is commonly utilized. Group of psychophysiological type of signals commonly used to measure the emotions are Electroencephalography (EEG, brain) (Murugallan, 2010), Electrocardiography (ECG, heart), Electromyography (EMG, muscular contractions), Electrooculography (EOG, eye dipole field), skin temperature, Galvanic Skin Response (GSR) or known as Skin Conductance (SC), etc.

The responses from bio-signals parameters are more accurate and reliable compared to the survey method, due to the tendency of people to lie or hide their feeling.

Electroencephalography (EEG): Electroencephalography is a medical imaging technique that reads scalp electrical activity generated by brain structures. The Electroencephalogram (EEG) is defined as electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and conductive media. Electroencephalography (EEG) is primarily utilized to acquire brain signal at certain position of the head. Despite being the most complex technique, EEG signals captured from the brain in Central Nervous System (CNS) have been proven to be able to provide informative characteristics respect to the emotional states.

Brain waves can be classified into five basic frequency band as in study: beta (>13 Hz), alpha (8-13 Hz), theta (4-8 Hz), delta (0.5-4 Hz) and gamma (32-64 Hz). Alpha is the resting state of the brain where the mental coordination is calmness. Beta is a ‘fast’ activity which happen when we are alert, focus, engaged in problem solving, assessment and decision making. Beta brainwaves are further divided into three bands: Lo-Beta (Beta 1, 12-15 Hz) thought of as a ‘fast idle’ or musing. Beta (middle Beta 2, 15-22 Hz) as high engagement. Hi-Beta (Beta 3, 22-38 Hz) is highly complex thought, integrating new experiences, high anxiety or excitement. Gamma brainwaves are the fastest part of brain waves, related to simultaneous processing of information from different brain areas. It passes information rapidly, in condition, the mind has to be calm enough to enable the access of the brain. Gamma was declared as “spare brain noise” until researchers discovered it was highly active especially in the states of universal love, altruism and the ‘higher virtues’. Delta waves are thought to emerge from the thalamus and are generally associated with three and four of the stages of sleep. The period which delta waves occur is often known as deep sleep. Theta brain waves occur during deep meditation and light sleep. It is the realm of your sub-consciousness experienced as drift off to sleep from Alpha and wake from deep sleep (Delta).

Brain waves change according to our movement and the environment. Slow brainwaves frequencies are dominant when we feel tired, sluggish or dreamy. Meanwhile, high frequencies are found to be dominant when we are in active thinking. The speed is measured in hertz (cycles per second) and they are divided into bands: slow, moderate and fast waves.

MATERIALS AND METHODS

Data acquisition: EEG can be measured by placing electrodes on scalp which usually has very small amplitude in microvolts (Teplan, 2002), thus, it will not give any harm to the subjects. Figure 2 shows the flow chart of EEG data acquisition from the initial until the final steps of human emotion recognition are done.

The experiment paradigm or protocol must be clearly defined before the data measurement can be started. All participants kept their body calm while sat on a comfortable chair during the entire emotion elicitation experiment. The placement of electrodes are based on the 10-20 international system as Fig. 3. The number of electrode used also depend on the researcher. Some of the researcher believed the frontal lobe point F_{p1}, F_{p2} and F_{pz} will respond aggressively when it comes on emotions.

Evoked techniques: The most prominent emotion induction technique for emotion recognition are predominantly based on pictures, sounds or clips that assumed to evoke certain emotional states, commonly in the valence/arousal space. Two of the databases most frequently used for that purposes are the International Affective Picture System (IAPS) database and the International Affective Digitized Sounds (IADSs) from University of Florida that include pictures and sounds labeled with valence and arousal values by subjects during large-scale experiments. More specifically, the images included in the IAPS database mostly picturize situations that evoke negative or positive feelings with low or high intensity.

Wang and Cheong used audio and video as a medium to induce and classify basic emotions elicited by movie scenes. Audio was classified into music, speech and environment signals. Various studies have been done to analyze the efficiency of music characteristics through application of accoustics. Rhythm, tempo, Mel-Frequency Cepstral Coefficients (MFCC), pitch, zero crossing rate are amongst common features to characterize affect in music listening. Koelstra present 40 videos in 40 trials from DEAP database to evoke the emotions.

Artifacts removal: The collected raw EEG data will go through the pre-processing stage to filter out all unwanted signals or artifacts it may have before the features are extracted. Subject artifacts are the unwanted physiological signals that may disturb the EEG signal. The artifacts in the recorded EEG may be coming from either the subject or other electronics influences. Technical artifacts such as AC power line noise can be decreased by maintain the electrode impedance <10 kΩ and by shorter electrode wires as shown in Table 2.

The artifacts which can be captured from the environment and psychophysiological signal including eye blinking are dominant below 4 Hz frequency, ECG

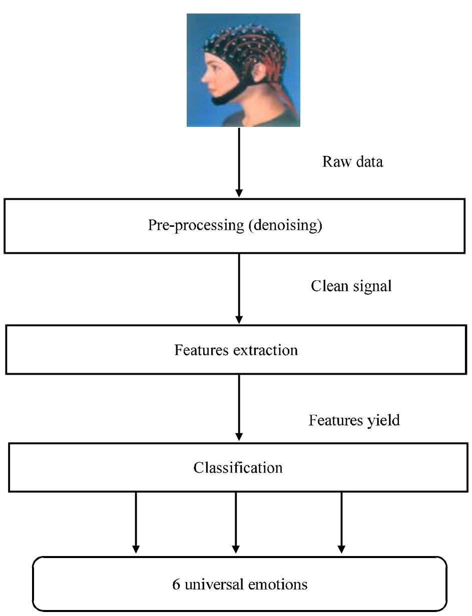

Fig. 2: Flowchart of EEG data acquisition

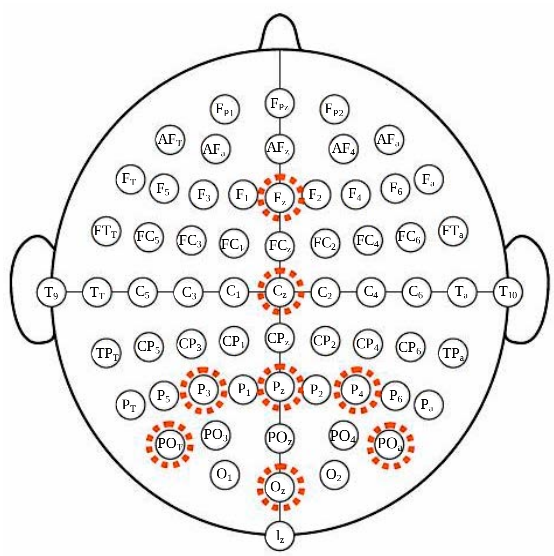

Fig. 3: The placement of electrodes based on the 10-20 international system

noise around 1.2 Hz, EMG larger than 30 Hz, movement, pulse and so on. Notch filter is usually used to filter the at 50/60 Hz power line noise. Table 2 shows some other the artifacts and the filtered frequency used to remove these artifacts.

Features extraction: Features extraction is the process to extract the signal features such as mean, variance, standard deviation, entropy and spectral power density from five frequency band, theta, beta, alpha and gamma as Fig. 4. There are many techniques for the features extraction methods: wavelet transform, Short-Time Fourier Transform (STFT), Multiwavelet Transform (MT) and statistical data.

Feature selection was a necessary process before performing any data classification and clustering. The objective of this process is to extract a subset of features by removing redundant features and maintaining the informative features.

Classifier: System or algorithm that arrange a group of data set into their classes is referring as a classifier. Some of the classification methods that are widely used in human emotion research include Support Vector Machine (SVM), Fuzzy Logic, Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Multilevel Training (MLT), Zero R, naive bayes, bayesian network, Multi Layered Perception (MLP), Linear Discriminant Analysis (LDA), etc.

The accuracy of a classification is usually assessed by comparing the classification results with some standard reference data (Congalton, 1991). Validation process is done to ensure the accuracy is maintained even in different experimental conditions. Survey method as the validation techniques have been widely used in many research. The accuracy or success rate will show the level of classifier competence (Congalton, 1991). The lower accuracy rate is not exactly a poor classifier. Some classifier needs a few advancement from the based-method to function superiorly. The classification accuracy may be maximized by choosing an optimal combination of input data layers (Russell, 1980).

Some examples of the accuracy rate of the classifier reported by other researchers are shown in Table 3. Darvishi and Ani report the accuracy rate by using adaptive neuro-fuzzy classifier 80.71%. The performance

Table 2: Artifacts in the EEG signals

Subjects	Technical
Minor body movements	Power line noise at 50/60 Hz
EMG	Impedance fluctuation
ECG (pulse, pace-maker)	Cable movements
Eye blinking	Broken wire contacts
Sweating	Exceeded electrode paste
	Low battery

Table 3: Accuracy rate of other classifier

Classifiers	Accuracy rate (%)
Adaptive Neuro-Fuzzy (ANF)	80.71
Artificial Neural Network (ANN)	85.90
Multilayer Perceptron (MLP)	97.00
Radial Basis Function (RBF)	98.00
Suport Vector Machine (SVM)	100.00

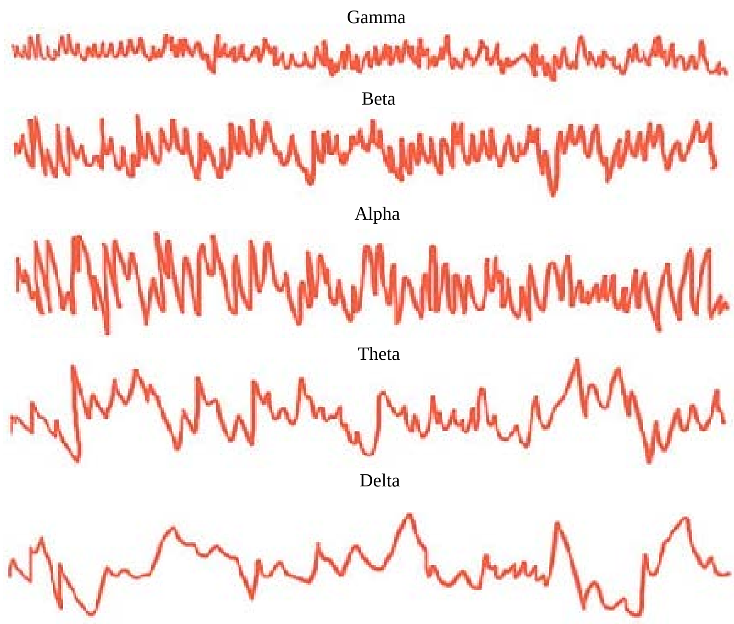

Fig. 4: EEG brain waves

of classification using Artificial Neural Network (ANN) gave a success rate of 85.9 % for distinguishing normal signals. The results of their study reported a classification accuracy approximately 97% for the Multilayer Perceptron (MLP) network based classifier and accuracy of 98% for Radial Basis Function (RBF) network. However, SVM (Zhong*et al.*, 2008) proved to be a powerful classification algorithm which is very useful when dealing with large number of features extracted and limited number of patterns training. The optimal method for classification have been used is SVM with the highest average accuracy rate 100% recorded (Asl *et al*., 2008).

Background study of SVM classifier: Many research report the advantages of using SVM as a classifier especially when deal with a large scale of experimental data. This study reviewed this classifier technique and the related works done by others that using SVM.

In machine learning system, SVM classifier are supervised models with algorithms engaged to analyze data and recognize patterns, used for classification. Given a set of data examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other.

SVM uses the concept of optimal hyperplane. The hyperplane will separates the data without error with the maximal distance between the data vector and the plane. The set of data are not always be separated by linear functions, the dimensionality increase with kernel functions is a common approach by using the SVM classifier. Vapnik introduce the SVM concept in 1992 during the COLT92 conference. The transformation of a linearly inseparable dataset in a new one that is linearly classifiable, increasing the number of dimensions using only the data from the original dataset. After this data transformation, it becomes possible to classify the original dataset using those new dimensions generated by the transformation. Hyperplane and the concept of kernel functions is used to increase the dimensionality.

Linear SVM: The idea proposed by Vapnik and Baudat of SVM was developed for linearly separable data. Suppose the training data is:

$$N:\{(x_1, y_1), (x_2, y_2),..., (x_N, y_N)\}$$

where, $x_i \in Rd$ and $y_i \in [\pm 1]$. In linear SVM, a linear separating hyper plane classifier is given by Eq. 1:

$$f(x) = sgn(w.x+b) \quad (1)$$

The maximum separating margin must have this hyperplane with respect to the two classes where:

$$H: y = w.x+b = 0 \quad (2)$$

$$H_1: y = w.x+b = +1 \quad (3)$$

$$H_2: y = w.x+b = -1 \quad (4)$$

Specifically, the hyperplane we need to find is and two hyper planes parallel to it and with equal distances to it, $H_1$and H_2 with the condition that there are no data points between them and the distance between H_1 and H_2 is maximized as Fig. 5. The distance between H_1 to H is Eq. 5 while H_1 to H_2 is Eq. 6:

$$\frac{|wx+b|}{\|x\|} = \frac{1}{\|w\|} \quad (5)$$

$$\frac{2}{\|w\|} \quad (6)$$

Therefore to maximize the margin, w must be minimize by Eq. 7:

$$|w| = w^T w \quad (7)$$

with the condition no data points between H_1 and H_2:

$$\text{Positive examples } y_i = +1,\ w.x+b \geq +1$$

$$\text{Negative examples } y_i = -1,\ w.x+b \geq +1$$

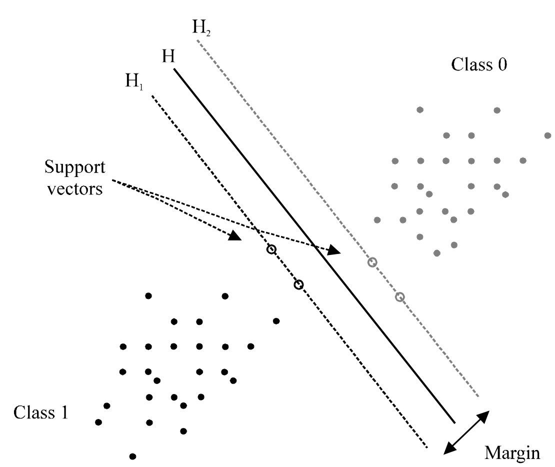

Fig. 5: SVM for generalization

and the maximal margin hyperplane can be calculated by minimizing the function (Eq. 8):

$$\Phi(w) = \frac{1}{2}(w.w) \tag{8}$$

The dataset that can be linearly separable, using the concept of maximal margin hyperplane without errors and the increase of dimensionality by SVM.

Non-linear and soft margin: The case of non-linearly separable input space, data inputs can be mapped to another high dimensional feature using non-linear function chosen and the data points will be linearly separable.

There are many ways to increase the dimensionality of a dataset and one method that is commonly use is Kernel Functions (KF). In a Hilbert Space, Kernel functions K(x, x') computes the similarity between two features x and x', being the common Kernel functions used: Linear, Polynomial and RBF Kernels. The dimensionality of a given dataset is possible to be increased by using any of these function and become linearly separable by using a SVM classifier.

RESULTS AND DISCUSSION

Related works on different types of SVM classifier: Although, using the same classification method, the accuracy is highly dependent on the feature extraction methods. The following review shows different accuracy achieved that is influenced by different feature extraction techniques.

Short-Time Fourier Transform (STFT) method and SVM classifier via RBF Kernel: Research of EEG signals by SVM via RBF Kernel transfer function during listening to music is compute by Yuan *et al*.. EEG data was collected from 26 healthy subjects. A 32-EEG channel from Neuroscan was arranged according to international 10-20 system was used. A ground electrode was located in the forehead. The sampling rate and filter bandwidth were set to 500 Hz and 1~100 Hz, respectively. An additional 60 Hz notch filter was employed to avoid the power-line contamination. All electrode impedances were kept below 10 kΩ for the EEG. EOG activity was also recorded to monitor the EEG artifact rejection.

They analyzed four basic emotional states following a 2D Valence Arousal Emotion Model including joy (positive valence and high arousal), anger (negative valence and high arousal), sadness (negative valence and low arousal) and pleasure (positive valence and low arousal). Sixteen clips from Oscar's film soundtracks were selected as stimuli. Each was edited into a 30-s music clips. The recorded EEG data were first preprocessed to removeartifacts and the artifact-free data were then divided into 16, 30 sec segments for each individual.

The features study were based on the spectral power changes, a 512-point Short-Time Fourier Transform (STFT) with a non-overlapped Hanning window of 1 sec was applied to each of 30 channel of the EEG data to compute the spectrogram. The power are divided into five frequency band, including delta, theta, alpha, beta and gamma. The spectral time series for each subject thus consisted of around 480 sample points.

Two major factors were tested: the types of features and the frequency bands of the EEG. Several feature categories were systematically tested in this study. First, individual spectral power from 30 scalp electrodes were used as the features: F_{p1}, F_{p2}, F_7, F_3, F_z, F_4, F_8, FT_7, FC_3, FC_z, FC_4, FT_8, T_7, C_3, C_z, C_4, T_8, TP_7, CP_3, CP_z, CP_4, TP_8, P_7, P_3, P_z, P_4, P_8, O_1, O_z, O_2 including A_1 and A_2 as reference point named PSD30. Next, the spectral power of the hemispheric asymmetry index was also adopted and extended from the previous study. Throughout the whole brain, there were 12 asymmetry indexes derived from 12 symmetric electrode pairs, namely F_{p1}-F_{p2}, F_7-F_8, F_3-F_4, FT_7-FT_8, FC_3-FC_4, T_7-T_8, P_7-P_8, C_3-C_4, TP_7-TP_8, CP_3-CP_4, P_3-P_4 and O_1-O_2. The asymmetry indexes were calculated either by power subtraction (power of [C_3-C_4]) or division (power of [C_3/C_4]) and labeled as differential asymmetry of 12 electrode pairs (DASM12) and rational asymmetry of 12 electrode pairs (RASM12), respectively. Lastly, the individual spectra of these 12 symmetric electrode pairs (24 channels) were also used as the features for emotion classification, named Power Spectrum Density of 24 channels (PSD24). The PSD24 was part of PSD30 without the electrodes along the midline (F_z, FC_z, C_z, CP_z, P_z and O_z).

This project employed SVM to classify the emotion label for each EEG segment. The basic idea is to project input data onto a higher dimensional feature space via a kernel transfer function which is easier to be separated than that in the original feature space. This study used LIBSVM Software (Chang and Lin, 2011) to build the SVM classifer and employed RBF kernel to nonlinearly map data onto a higher dimension space.

Feature selection was to extract a subset of features by removing redundant features and maintaining the informative features. This study adopted F-score index, one of statistical methods to measure the ratio of between and within class variance for sorting each feature in descending order accounting for discrimination different

EEG patterns (e.g., the larger the F-score, the greater the discrimination power). Several factors have been investigated in the classification stage which are as follows:

- Types of features
- Frequency bands of the EEG
- Types of classifiers
- Number of features
- Number of electrodes

Table 4 shows the averaged classification performance of SVM using four feature types DASM12, RASM12, PSD24 and PSD30. Based on this Table 4, the averaged performance using differential asymmetry of 12-elctrodes pair (DASM12) stated the maximum accuracy of 82.29% (±3.06%) from all evoked by music treatment.

Wavelet Transform (WT) and Gaussian SVM classifier: Jatupaiboon research on emotion classification using minimal EEG channels and frequency bands shows that frontal pairs of channels give a better result than the other area of brain and high frequency bands give a better result than low frequency bands. Reducing number of pairs of channels from 7 to 5 state almost the same accuracy and cut low frequency bands in order to minimize computation time.

Researcher used 100 pictures from Geneva Affective Picture Database (GAPED) (Dan-Glauser and Scherer, 2011) to elicit emotion. The 50 pictures with high valence score are selected to be positive stimuli while the other 50 pictures with the lowest valence score to be negative stimuli. The 14 channels EMOTIV (i.e., AF_3, AF_4, F_3, F_4, F_7, F_8, FC_5, FC_6, P_7, P_8, T_7, T_8, O_1 and O_2) to record EEG signal. The experiments take about 30 min. There are 11 participants involved in this experiment. They used Blind Source Separation (BSS) to filter (EOG) and (EMG) artifact that contaminate the EEG signal using EEGLAB (Delorme and Makeig, 2004).

The EEG signals are extracted to 5 frequency bands that are delta, theta, alpha, beta and gamma by wavelet transform. The feature computed is power spectrum from each band. The features are normalized between 0 and 1 to reduce inter-participant variability. The

Table 4: Average results of standard deviation by SVM

	EEG frequency band					
Feature types	Delta	Theta	Alpha	Beta	Gamma	All
DASM12	69.91	68.27	66.94	58.83	57.35	82.29 (±3.06%)
RASM12	50.91	51.39	56.95	50.29	47.61	65.81 (±5.09%)
PSD24	51.02	53.27	54.61	55.42	56.80	69.54 (±5.10%)
PSD30	53.38	55.61	56.64	58.71	59.54	71.15 (±4.88%)

total features extracted was 4400 samples. The samples are labeled with positive or negative depending on type of stimulus.

Gaussian SVM with 10 fold cross-validation is used as classifier to compute accuracy. SVM implementation is done by using LIBSVM (Chang and Lin, 2011). They compare the accuracy between raw EEG signal and the signal after artifact filtering using all features. They found that the signal after filtering using this method gives better accuracy from that is 85.41%. Varying pair of EEG channels, they compare accuracy among each pair of channels (i.e., AF_3-AF_4, F_3-F_4, F_7-F_8, FC_5-FC_6, P_7-P_8, T_7-T_8 and O_1-O_2) for all frequency bands. They found that a pair of F_7-F_8 gives the highest accuracy at 66.14% and most of frontal pairs give higher accuracy than the other area from Fig. 6. Their conclusion is consistent that frontal lobe is more related to Valence emotion than the others (Schmidt and Trainor, 2001).

Varying frequency bands, they compare accuracy among different frequency bands for all channels. Gamma and Beta give accuracy at 81.91 and 80.64%, respectively that is higher than the other bands as Fig. 7. They conclude that the higher frequency bands related to Valence emotion than low frequency.

From their research works, the accuracy rate totally of SVM classifier is about 85.41%. They also found that frontal pairs of channels give higher accuracy than the other area especially pair of F_7-F_8 that gives the highest accuracy at 66.14%.

Multiwavelet Transform (WT) and Multiclass Least Squares Support Vector Machine (MC-LS-SVM) Classifier: Bajaj, research on human emotion classification from EEG signals using Multi-wavelet

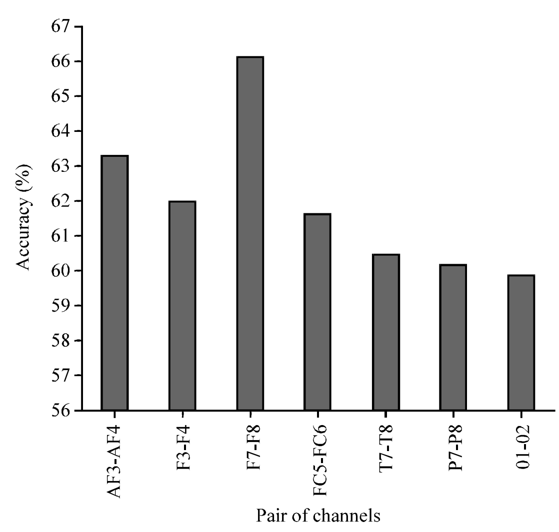

Fig. 6: Accuracy from each pair of channels

Transform (MT) reported high accuracy rate of 91.04% by Multiclass Least Squares Support Vector Machine (MC-LS-SVM) classifier.

The EEG signals were collected from 8 healthy subjects with equivalent gender of 4 males and 4 females during audio-video stimulus. A 16-channel of BIOPAC system in compliance to the international 10-20 system was used for recording of EEG signals. The sampling frequency of EEG signals was 1000 Hz. The different ways of inducing emotions are: visual includes images and pictures (Chanel *et al*., 2009), recalling of past emotional events, audio may be songs and sounds, audio-video includes film clips and video clips (Murugappan *et al*., 2009).

This study examined four basic emotional states following a 2D valence-arousal emotion model including happy, neutral, sadness and fear. In the experiment, 3 audio-video stimulus with 5 trials of each emotion from eight subjects with F_3/F_4 channel of EEG signals were used. The 480 EEG signals were yield with the duration of 2 sec.

In preprocessing stage, eight-order of Butterworth band pass filter is applied with a bandwidth 0.5-100 Hz

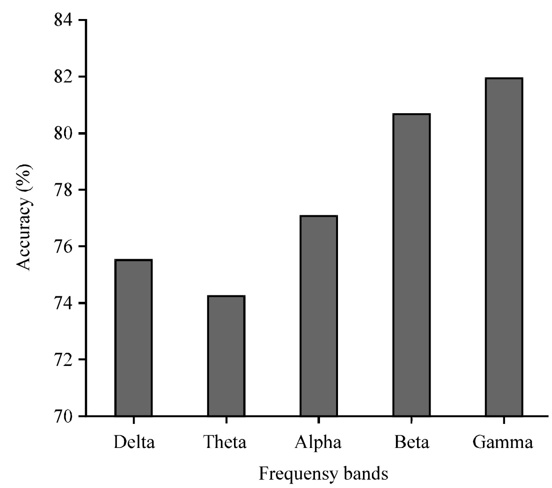

Fig. 7: Accuracy from different frequency bands

have been used for removing noises and artifacts. The 50 Hz notch filter is employed to remove the power line contamination.

The sub-signals obtained by multi-wavelet decomposition of EEG signals are plotted in a 3D phase space diagram using Phase Space Reconstruction (PSR). Three famous multi-wavelets transform are employed to extract the EEG components: Gernoimo-Hardin-Massopust (GHM) (Geronimo *et al*., 1994), Chui-Lian (CL) and SA4. They compute mean and standard deviation of euclidian distances from 3D phase space diagram. These features have been used as input features set for MC-LS-SVM together with the Radial Basis Function (RBF), Mexican hatwavelet and Morlet wavelet kernel functions for classification of emotions.

The classification accuracy (%) with GHM, CL and SA4 multi-wavelets for RBF kernel, Mexican hat and Morlet wavelet kernel functions of the MC-LS-SVM classifier for emotion classification are shown in Table 5. Multi-wavelet decomposition of EEG signals has better classification accuracy as compared to without multiwavelet decomposition. They shows classification results of MC-LS-SVM classifier with CL multiwavelet perform 91.04% accuracy for classification of emotions by Morlet wavelet kernel function.

Fast Fourier Transform (FFT) and SVM classifier via kernel functions: Naji *et al.* (2012) report the highest accuracy rate classification by SVM is 93.80% on emotion classification based on Forehead Bio-Signals (FBS) in music listening. Twenty two healthy subjects were involved to listen to the music excerpts for classes soothing, engaging, annoying and boring as Fig. 8.

The electrode placement area was cleaned by using alcohol swab. The signals is acquired from three different forehead location: left Temporalis, right Temporalis and Frontalis by BIOPAC System. The sampling frequency and amplifier gain were selected at 256 Hz and 5000, respectively. The data were recorded during 60 sec silent

Table 5: The classification accuracy (%) with different Kernels of the MC-LS-SVM classifier using different multi-wavelets

Multi-wavelet	Kernel function (parameters)	Happy (%)	Neutral (%)	Sad (%)	Fear (%)	Total accuracy (%)
Without multi-wavelet	RBF	76.94	71.11	68.05	71.66	71.94
	Mexican hat	77.50	70.27	67.22	71.38	71.59
	Morlet	78.33	71.11	69.72	70.55	72.42
GHM	RBF	84.16	91.66	90.83	85.83	88.12
	Mexican hat	69.17	69.44	68.33	78.33	71.31
	Morlet	85.83	90.83	91.67	86.67	88.75
SA4	RBF	88.33	70.00	80.33	79.17	79.46
	Mexican hat	87.50	75.00	73.06	65.83	75.35
	Morlet	88.33	75.00	82.50	80.00	81.46
CL	RBF	87.50	86.67	88.33	96.67	89.79
	t	78.33	76.67	78.33	93.33	81.66
	Morlet	88.33	86.67	90.83	98.33	91.04

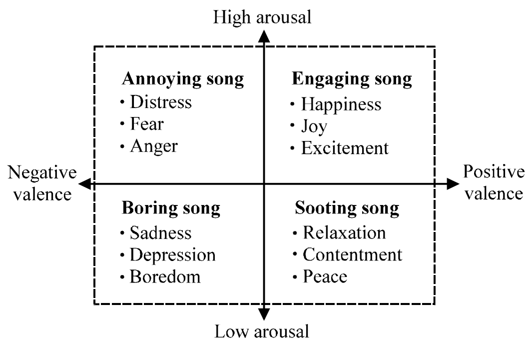

Fig. 8: Arousal-Valence Model of emotion for the excerpts music

followed by 120s excerpt musics. A questionnaire were completed by all subjects to validate the success of emotion induced.

The raw EEG data were filtered with band-pass of 1-100 Hz and band-stop of 47-53 Hz. Fast Fourier Transform (FFT) is used to find features of relative power, spectral entropy and mean in the frequency band: theta (θ : 4-7 Hz), slow alpha (α_1: 8-13 Hz), fast alpha (α_2: 11-13 Hz), alpha (α: 8-13 Hz), slow beta (β_1: 13-19 Hz), fast beta (β_2: 20-30 Hz), beta (β: 13-30 Hz) and gamma (γ: 31-50 Hz).

All the four emotional state in Valence-Arousal are classified by employing two parallel SVM as arousal and valence classifiers. The input of the classifier is obtained by features selection algorithm of fuzzy-rough model. The data projection used a radial basis function as a kernel function in the SVM classifiers (Quan and Ren, 2010a). Arousal and valence classifier stated the maximum accuracy of 93.8 and 92.43%, respectively. While, the averaged subject-independent classification accuracy of 93.80, 92.43 and 86.67% for arousal classification, valence classification and classification of four emotional states in Arousal-Valence space, respectively.

Fast Fourier Transform (FFT) and SVM classifier: Cao on emotional recognition from Chinese emotional words found the accuracy rate by SVM is 48.78% from EEG signals. They also compare the classification method between SVM and Linear Discriminant Analysis (LDA) where LDA give better accuracy rate in this case, 57.04%. They found the accuracy rate between different genderis 48.18% for females and 49.58% for males. From ESA Pro/Basic system, twenty one electrode channels are placed on the scalp with a reference electrode at the right mastoid according to the international 10-20 standard.

They tend to choose words with emotional intensities and frequencies are relatively higher than others, although, it have more difficulties in inducing emotions. All the emotional words were taken from modern chinese dictionary and filter out some emotional words and obtain 945 high frequencies emotional words (469 positive words, 476 negative words) (Quan and Ren, 2010b).

The features are extracted by Fast Fourier Transform (FFT) at sampling rate of 200 Hz. Features are divide into three frequency band: theta, alpha (8-13 Hz) and beta (13-20 Hz). The extraction of the features are done by two different method: time-frequency and time domain analysis. They calculate the cross-correlation features (Mushа*et al*., 1997) for signals between potentials at four EEG channels (F_{p1}, F_{p2}, F_3, F_4) within the alpha range (8-13Hz). Principal Component Analysis (PCA) is used to reduce the large number of variables to fewer components (Lagerlund *et al*., 1997). They compute PCA features for the signals within beta range at the same four EEG channels (F_{p2}, F_{p2}, F_3, F_4). Average recognition rates over all subject of 48.78% using SVM classifier and 57.04% for the LDA classifier.

High Order Crossing (HOC) an SVM classifier: Emotion Recognition Using Higher Order Crossings (HOC) of features extraction for EEG signals are proposed by Petrantonakis. The EEG signals is acquired from single electrode and pair-electrode channels, namely F_{p1}, F_{p2} and a bipolar channel of F_3 and F_4 positions according to 10-20 system. The signal were running by g.MOBI-lab with filter frequency 0.5-30 Hz and sensitivity of 100 μV. The 16 bit resolution with A/D converter and sampling frequency of 256 Hz are used. Ten order of IIR Butterworth band-pass filter used to isolate the alpha and beta waves.

The EEG signal were collected from 16 healthy volunteers under emotion evocation with visual inputs (pictures with emotion-related facial expressions) to classified 6 universal emotion: happiness, surprise, anger, fear, disgust and sadness. This setup followed the Mirror Neuron System (MNS) concept (Rizzolatti and Craighero, 2004).

HOC analysis was employed for the feature extraction scheme and a robust classification method, namely HOC-emotion Classifier (HOC-EC) was implemented testing four different classifiers: Quadratic Discriminant Analysis (QDA), k-Nearest Neighbor (k-NN), mahalanobis distance and SVM. From the author previous approaches, the Hoc-Emotion Classifier (HOC-EC) is quite attractive due to its superiority in the emotion recognition power for a combination of up to six distinct emotions.

Two types of features were extracted from a single-channel and from combined-channels, respectively. HOC-EC appears to be a better method, achieving accuracy of 62.3% by QDA and 83.33% by SVM for the single-channel and combined-channel cases, respectively.

Dual-Tree Complex Wavelet Packet Transform (DT-CWPT) and SVM classifier: Naser proposed an improvement of wavelet transform features method named Dual-Tree Complex Wavelet Packet Transform (DT-CWPT) for the SVM classification.

EEG signals of 32 participants are recorded as they watched the 40 selected music videos. Each videos were rated by the participants in terms of arousal, valence, like/dislike, dominance and familiarity. They use DEAP database for emotion classification. 32-channel of electrode are placed according to the 10-20 international system.

Discrete Wavelet (DWT) (Murugappan *et al*., 2009) transform are used to provide time-frequency information for feature extraction from EEG signals. The features are extracted by the frequency band: theta, alpha, low-beta, high-beta and gamma. The energy features from 32 EEG electrodes and difference between the energy of all the symmetrical pairs of electrodes on the right/left hemisphere are extracted to measure asymmetry in the brain activities due to emotional stimuli. The total number of trials for 32 participants watching 40 videos each is 1280 ware as total number of features of a trial for 32 electrodes is 782.

All the features not contain the same amount of information and some of them may be redundant and not be useful for discrimination purpose. A few features selection are used, Singular Value Decomposition (SVD), QR Factorization with Column Pivoting (QR_{CP}) and F-ratio based method to train the SVM to classify emotion for each video. Energy features used for classification contains both the time and frequency information of EEG signals. Radial-Basis Kernel (RBF) is used for classification in a leave-one-out cross validation scheme for the SVM classifier. The average classifications rate are 64.3% for valence, 66 .2% for arousal, 70.2 % for like and 68.9% for dominance.

Wavelet transform, statistical and hjorth parameter and Linear Support Vector Machine (LSVM) classifier: Singh report the accuracy rate of negative emotions: sad and disgust through EEG signals are 83.32 and 82.55%, respectively using Linear Support Vector Machine (LSVM) classifier and 78.04 and 76.31%, respectively for k-Nearest Neighbour (k-NN) classifier.

Eights subjects involved, 4 males and 4 females. EEG data evoked by audio-visual stimuli for emotion recognition were collected to classify the EEG signals into two corresponding emotions, sad and disgust, both are negative emotional states.

The EEG signals have been recorded using the NEUROWIN EEG amplifier with a sampling rate of 250 Hz from four electrodes at F_3, F_4, F_{p1} and F_{p2}. The signals are filtered out by pre-processing in the MATLAB environment using an elliptical band pass filter of order 10 and bandwidth 4-32 Hz. The bandwidth of the filter being chosen are theta and alpha that lie within the chosen range.

Features have been extracted using wavelet transform, statistical parameters (Islam *et al*., 2013) and Hjorth parameter estimation as Table 6. These method are

Table 6: Features yielded from different method

Features methods	Features
Wavelet Transform (WT) (Daubechies wavelet)	Wavelet function f(t)
Statistical	Mean Standard deviation Entropy Recoursing Energy Efficiency (REE)
Hjorth	Time domain of EEG signals-signal: Power Mean Frequency Bandwidth

Table 7: Summary of the related works by SVM classifier

Classifier types	Features extraction method	Features extracted	Electrode number/Location	Accurancy rate (%)
SVM via RBF Kernel	STFT	Spectral power for delta, theta, alpha, beta and gamma band	F_{p1}, F_{p2}, F_7, F_3, F_4, F_8, FT_7, FC_3, FC_4, FT_8, T_7, C_3, C_4, T_8, TP_7, CP_3, CP_4, TP_8, P_7, P_3, P_4, P_8, O_1 and O_2	92.73 (±2.09)
Gaussian SVM	Wavelet Transform (WT)	Power spectrum for delta, theta, alpha, beta and gamma	EMOTIV/14 channels/AF_3, AF_4, F_3, F_4, F_7, F_8, FC_5, FC_6, P_7, P_8, T_7, T_8, O_1 and O_2	85.41
MC-LS-SVM with Radial Basis Function (RBF), Mexican hat and Morlet kernel functions	Multiwavelet Transform (MT)-GHM, CL, SA4	Mean, standard deviation of Euclidian	16 channel (biopac.inc)	91.04
SVM via kernal functions	FFT	Power, spectral entropy andmean of theta, slow alpha, fast alpha,alpha, slow beta, fast beta, beta and gamma	16 channel (biopac.inc)	93.80
SVM&LDA	FFT	Time-frequency analysis, time domain analysis for theta, alpha and beta	21 electrode (ESA Pro/Basic system)	48.78
HOC-EC: QDA, k-NN, Mahalanobis distance and SVM	HOC	Alpha and beta	F_{p1}, F_{p2}, bipolar channel (F_3 and F_4)	83.33
SVM via RBF Kernel	DT-CWPT	Time frequency analysis of delta, theta, alpha, beta and gamma	32 channel	67.4
LSVM	Wavelet transform, statistical and Hjorth parameter	Mean, SD, power, theta, alpha	F_3, F_4, F_{p1} and Fp2NEUROWIN	Sad: 78.04, disgust:76.31

conducted to optimize the classification accuracy, time computation, number of needed and computational cost of classification.

Conclusively, LSVM classifier is found to perform most efficiently for negative emotion classification compare to the k-NN using these feature methods (Table 7).

CONCLUSION

Classification is one of the important steps in pattern recognition. Through the classification process, the pattern can be classified into intended results. One of the most popular classification methods is based on SVM classifiers. SVMs have become the method of choice to solve difficult classification problems in a wide range of application domains. They are chosen because of two properties: SVMs find solutions of classification problems that have 'generalization in mind' and they are able to find non-linear solutions efficiently using the "kernel trick".

The first property leads to good generalization performance even in case of high-dimensional data and a small set of training patterns. This is very relevant for EEG applications since, we typically have many features but only a relatively small set of trials per class. While this SVM property is useful to reduce the "curse of dimensionality" problem by reducing the risk of over-fitting the training data.

The second property is important to solve difficult problems which are not linearly separable. A binary (or two-class) classification problem is called linearly separable, if a "hyperplane" can be positioned in such a way that all exemplars of one class fall on one side and all exemplars of the other class fall on the other side. In case of two feature dimensions, the "hyperplane" corresponds simply to a line in case of three features, the hyper-plane corresponds to an actual 2D plane. The term "linear" means that the separating entity is "straight", i.e., it may not be curved. In difficult classification problems, optimal solutions may only be found if curved (non-linear) separation entities are allowed. In SVMs non-linear solutions can be efficiently found by using the "kernel trick": the data is mapped into a high-dimensional space in which the problem becomes linearly separable. The "trick" is that this is only "virtually" done by calculating kernel functions. For problems with high-dimensional feature vectors and a relatively small number of training patterns, non-linear kernels are usually not required. This is important for EEG applications because only linear classifiers allow to interpret the obtained values in a meaningful way for visualization.

The accuracy rate are the point to measure the level of the classifier when it respond on separating our data to its classes. This rate are influence by many factor from the beginning steps of data acquisition, de-noising and features extraction techniques. Equipment used also give an affect since, the characteristics and the limitation may be not the same for others. While, some researcher do the pre-processing of de-noising with special methods such as spatial, Gaussian, Morlet and etc. The same thing happen for the features extraction stage where a better techniques such as wavelet transform, discrete wavelet transform, FFT and SFFT are used widely in this applications. However by using this SVM classifier, the experiment success to maintain the higher accuracy rate because it has good generalization performance and the same algorithm of others may be used to solves a variety of problems with little tuning.

This review has been made to demonstrate the relationship between various ways of pre-processing data, method selection especially in the feature extraction level to the accuracy rate of the SVM classifier. Table 7 shows the summary of related works review by researchers that used SVM as a classifier.

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