THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

ENTROPY BASED METHODS TO ANALYZE SINGLE CHANNEL ELECTROPHYSIOLOGICAL BRAIN ACTIVITIES IN DISCRIMINATING EMOTIONAL STATES

Master's Thesis

SÜHEYLA AHSEN YILDIRIM

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This is to certify that we have read this thesis and we find it fully adequate in scope, quality and content, as a thesis for the degree of Master of Science.

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ABSTRACT

ENTROPY BASED METHODS TO ANALYZE SINGLE CHANNEL ELECTROPHYSIOLOGICAL BRAIN ACTIVITIES IN DISCRIMINATING EMOTIONAL STATES

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Bioengineering Program

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Recently, there is an increasing attention for electroencephalogram-based (EEG-based) emotion recognition since it is applicable to the fields of healthcare, games, e-learning systems and brain-computer interface (BCI) and also since it is successful to reflect human's real feelings.

The aim of this study is to review the papers which were published SCI-Indexed journals in last 10 years with respect to EEG analysis for emotion recognition and to compare each other by means of physiological meaning of results; finally to define the best EEG analysis approach, the best stimuli type and the best classification method with the high accuracy by grouping them in terms of feature extraction methods, stimuli types, classification methods.

Key Words: EEG, Emotion Recognition, Entropy

ÖZET

DUYGU DURUMU AYRIŞTIRMASINDA TEK KANALLI ELEKTROFİZYOLOJİK BEYİN AKTİVİTESİ ANALİZİ İÇİN ENTROPİ TABANLI METHODLAR

Süheyla Ahsen YILDIRIM

Biyomühendislik Programı

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Duygu tanıma araştırmaları, sağlık alanında sayısal tanı desteği sağlamak, beyin-bilgisayar ara-yüzlerinin geliştirilmesine katkıda bulunmak ve sanal oyunların veya reklam araçlarının etkisinin ölçülmesi için yapılmaktadır. Bu çalışmalarda vüdunun duygulanım durumu fMRI görüntüleme tekniği veya EEG ölçümleri ile yapılmaktadır.

Bu tez çalışmasının amacı; son 10 yıl içinde yayınlanmış ve EEG tabanlı duygu tanıma araştırmalarını derlemek ve uyaran tipi (ve veri tabanları), özellik elde etme yaklaşımları ve sınıflandırma yöntemleri açısından gruplandırarak en elverişli uyaran tipini, en başarılı EEG analiz yaklaşımını ve en yüksek doğruluğu sağlayan sınıflandırma yöntemini tespit etmektir.

Anahtar Kelimeler: EEG, Duygu Tanıma, Entropi

CONTENTS

FIGURES

ABBREVIATIONS

BVP	:	Blood volume pulse
CSEA	:	Center for Emotion and Attention
DEAP	:	The Database for Emotion Analysis using Physiological Signals
DWT	:	Discrete Wavelet Transform
EEG	:	Electroencephalography
ELM	:	Extreme Learning Machine
EOG	:	Electro-occulogram
FFT	:	Fast Fourier Transform
fMRI	:	Functional Magnetic Resonance Imaging
GSR	:	Galvanic Skin Response
HCI	:	Human-Computer Interface
IADS	:	International Affective Digitized Sound system
IAPS	:	International Affective Picture System
IFECN	:	International Federation in Electroencephalography and Clinical Neurophysiology
JAFFE	:	The Japanese Female Facial Expression
MEG	:	Magneto-encephalogram
OFC	:	Orbitofrontal Cortex
PET	:	Positron Emission Tomography
POFA	:	The Pictures of Facial Affect
SP	:	Spectral Power
SVM	:	Support Vector Machine
WE	:	Wavelet Entropy
VAD	:	Valance-Arousal-Dominance

1. THE GOAL OF THE THESIS

The main goal of this thesis is to

1. Define available stimulus types could be used to mediate the brain in obtaining emotional electrophysiological measurements,
   1.1 List international data bases including these emotional stimuli.
2. Compare studies, presented for emotion recognition by using EEG analysis with respect to their classification performance in accordance with both stimulus type and feature extraction method as well as classification approach.
3. State the parameters having the crucial role in computing performance in classification of emotional states,
4. Propose the best feature extraction method in single channel EEG analysis focused on detection of particular emotional state,
5. Propose the most useful emotional stimulus and data base.
6. Present the most useful classification approach in obtaining meaningful and robust results in this field.
7. State the role of entropy based feature extraction methods in the field of emotion recognition driven by EEG analysis depending on emotional stimulus and experimental paradigm.

2. INTRODUCTION

Introduction of the thesis starts with description of the emotion and emotion theories, after that, definition of EEG and finally emotional stimulus types.

Emotion is a feeling that occurs naturally rather than a voluntary event. Human consciousness and the interactions with other people in daily life are significantly affected by that feeling (Jerritta, 2011). Researches show that there is conduction of electrical impulses between the brain and the body which emotion's occurrence causes. When we experience an emotion (for example, the realization of danger), the brain is conducting involuntary electrical impulses and it causes some physiological changings such as rapid heartbeat and breathing, sweating, muscle tension (McNaughton, 1989; Hurst, 2012).

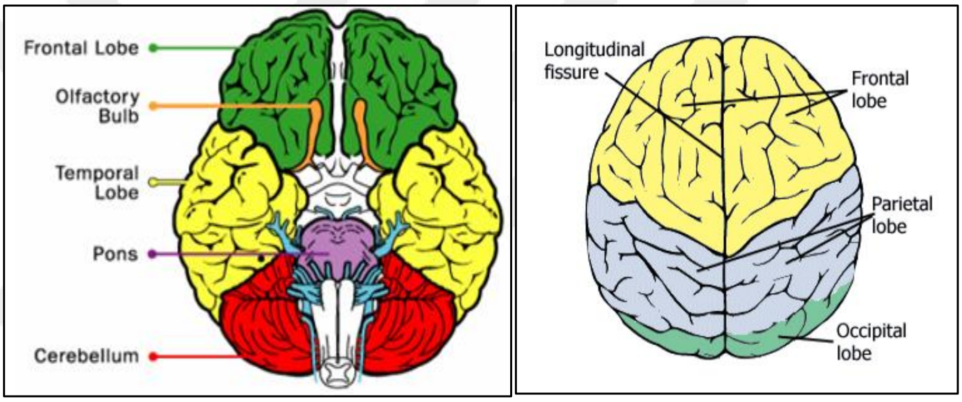
Recently, emotion recognition researches have been increased and many methods have been developed that could be applied Human-Computer Interface (HCI) in order to detect human emotion state and reactions (Petrantonakis, 2010). Since improved and modern HCI could be integrated to fields such as education, entertainment, communication, etc., it could allow us to develop better applications that could react more naturally and easily, or could produce output according to human emotions (Kolakowska, 2010; Liu, 2012). For e.g. if the interface understands the student's emotional state, it could provide more appropriate learning for them during online learning. For better detection of emotions, it is needed to extract appropriate features (Jenke, 2014; Jerritta, 2011).

These extraction methods are based on different data types such as facial expression, gestures, speech, voice, keyboard, mouse, touch screen, handwriting, physiological signals and also functional brain imaging techniques such as, Magneto-encephalogram (MEG), Positron Emission Tomography (PET), functional Magnetic Resonance Imaging (fMRI) or electroencephalography EEG, etc. However, in terms of being less expensive, less invasive and much more available than other systems, EEC has obvious advantages to work with for feature extraction (Petrantonakis, 2010; Yuankui, 2005).

The brain has three sections named cerebrum, cerebellum, and brain stem. The cerebrum obtains conscious awareness of sensation, complex analysis, and expression of emotions and behavior. The cerebrum consists of left and right hemisphere. Each cerebral hemisphere is formed of four lobes:

a. **Frontal lobe:** Includes motor area
b. **Parietal lobe:** Includes sensory area
c. **Temporal lobe:** Includes area of hearing & memory
d. **Occipital lobe:** Includes area of vision

Figure 2.1: Major external parts of brain

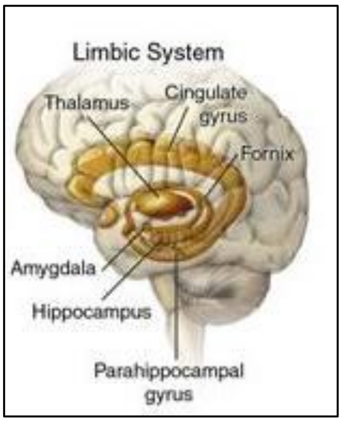


Source: Purves et al., 2001

Voluntary movements of muscles and balance maintaining are controlled by the cerebellum. Because of surface position of cerebral cortex, electric activity of it has the highest influence to EEG. (Purves, 2001).
There is a structure called amygdala which is a small and like almond as a shape and it is in deep of the temporal lobe and parts of limbic system which is thought that emotions are derived by. The hypothesis that the amygdala is related the blood pressure and heart rate changes contained in “fear learning”.

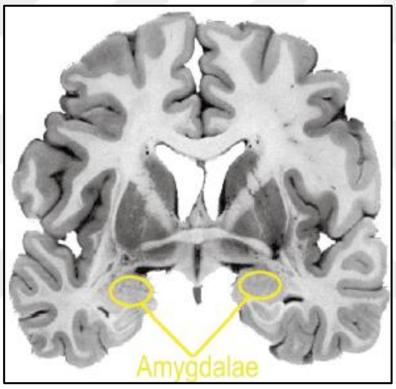
According to researches that have been done since many years showed that the part of brain Insula is related to emotion disgust, Orbitofrontal cortex (OFC) is related to anger, Anterior cingulate cortex (ACC) is related to sadness (Hurst, 2012; Lindquist, 2012; Davis, 2001).

Figure 2.2: Limbic system



Source: M. Teplan et al., 2012

Figure 2.3: Human amygdalae



Source: M. Teplan et al., 2012

If we would like to split the major theories in terms of their motivation it could be three major categories:

- **a.** Physiological
- **b.** Neurological
- **c.** Cognitive

Physiological theories say that responsible for emotions' occurrence are responses within the body. Neurological theories suggest that emotional responses are caused by activity within the brain leads. Cognitive theories say that mental activities lead to the formation of emotions.

- **a.** The James-Lange Theory of Emotion
- **b.** The Cannon-Bard Theory of Emotion
- **c.** Schachter-Singer Theory

d. Cognitive Appraisal Theory

Emotions play a powerful role on human behavior. Sometimes our strong emotions can lead us to decide to take actions that we might not normally do or ignore things that we normally enjoy. To understand what leads us to get these feelings, researchers, philosophers, and psychologists have suggested many variable theories.

As an example to physiological theory of emotion is the James-Lange theory. This theory is proposed by psychologists William James and Carl Lange. This theory says that when we physiologically react to some events, emotion occurs.

This theory also says that what causes to a physiological reaction is an external stimulus we see. Those emotional reactions vary to how we interpret the physical reactions of us. For instance, let imagine we are walking in the woods and suddenly we see a bear. We start to tremble and our heart starts to race.

What the James-Lange theory says that we will decide that we are afraid interpreting our physical reactions. According to the James-Lange theory, we feel frightened because of trembling; not trembling because of being frightened.

The Cannon-Bard theory of emotion is the second example to physiological theory. Cannon was not agree with the James-Lange theory on many ways. He said, we may show physiological reactions related to emotions without feeling any emotions. For instance, our heart may race because of having been exercising; not because of being afraid.

Physical states produce emotional responses much quickly according to Cannon. People generally feel fear before physical danger occurred and afraid symptoms start also before danger (breath and heart rate change).

During 1930s Philip Bard expands the Cannon's theory (1920s), and they shared the thought of feeling emotions and physiological reactions (sweating, shaking and tension etc) to them occurred simultaneously.

They also indicated that psychological and physical reactions happens at the same time without triggering other one to occur, and this process occurs by thalamus sending signal to brain as response to stimulus.

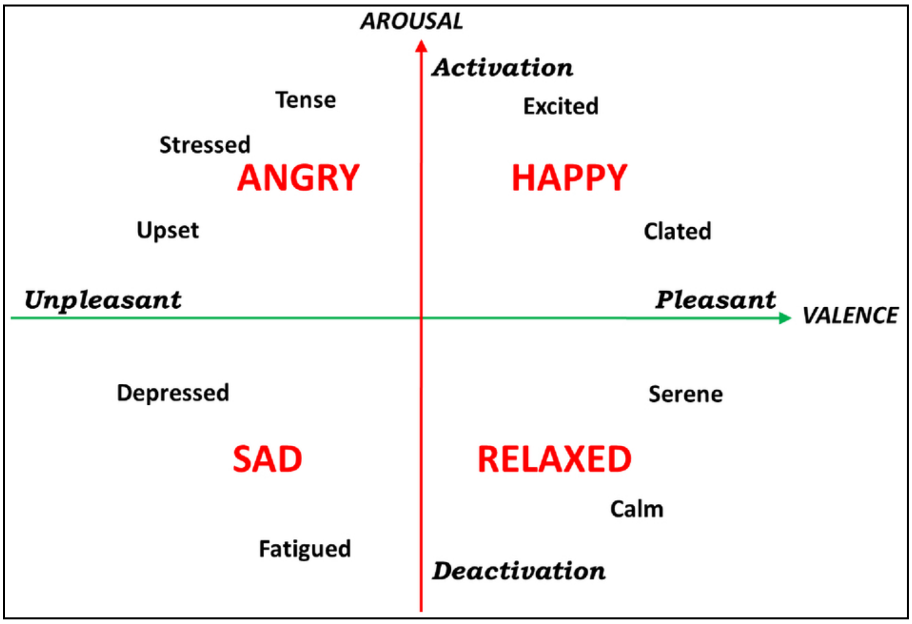
Schachter-Singer put forward other theory that suggests after physiological arousal, person must understand the reason for arousal and its related emotion. The stimulus creates physiological responses which turn into emotion after labeling and cognitively interpreting these responses.

The Schachter-Singer also claims the similar theory with Cannon-Bard that suggests varying emotions can be produced by physiological responses. For instance; during an exam varying heart rate and sweating may correspond to anxiety.

Cognitive Appraisal Theory is another theory for emotions, which claims that thinking should occur before the person experiences the emotion. In this theory, emotion will occur as stimulus, thoughts, physiological responses and emotions respectively. For instance, if you face with wild animal, you think you are in danger and this thought produce fear and other physical reactions, then they turn into emotion.

In the field of emotion researches, classifying an emotion from another is a debated issue. Researchers have been studied on classification of emotions from different point of view such as being discrete and having different constructs or being able to be characterized based on dimensional features when they are grouped.

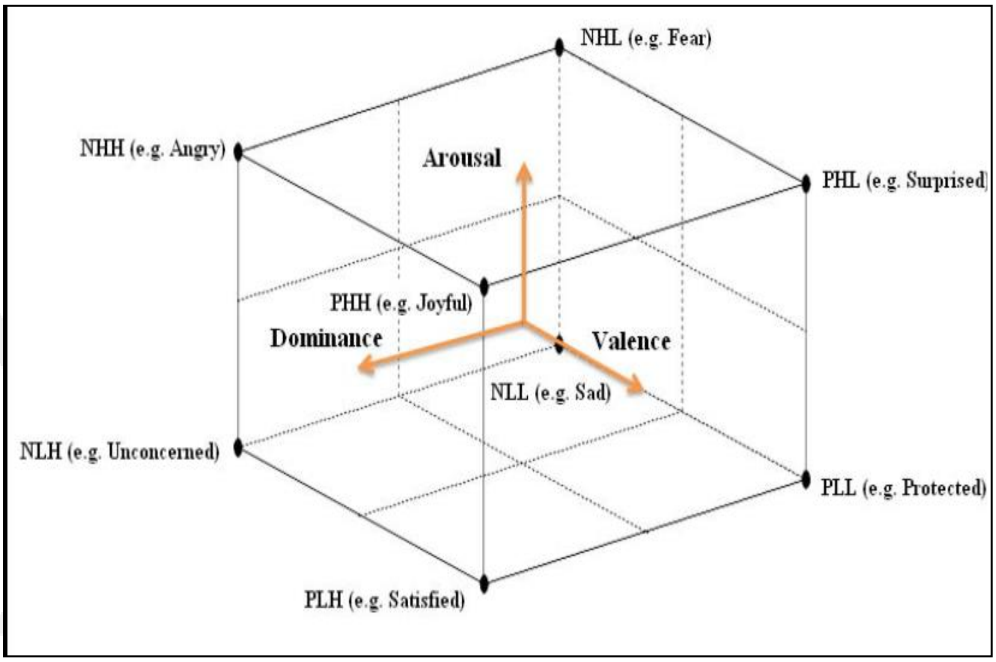
Figure 2.4: Russell's circumplex model



Source: Liu et al., 2012

The circumplex model which was proposed Psychologist James Russell in 1980 is a conceptualized 2-dimensional continuous space where the horizontal and vertical axes correspond to the degree of valence (pleasure) and arousal, respectively. Emotions can be grouped in terms of degree of arousal and valence as illustrated in Figure 2.4. Using this model, the degree of any of the aforementioned discrete emotional state can be measured.

Figure 2.5: 3D Emotion Classification Model



Source: Liu et al., 2012

In 3D emotion classification model protected emotion is related to PLL which means positive-low arousal-low dominance;

Satisfied is related to PLH which means positive-low arousal-high dominance;

Surprised is related to PHL which means positive-high arousal-low dominance;

Joyful is related to PHH which means positive-high arousal-high dominance;

Sad is related to NLL which means negative-low arousal-low dominance;

Unconcerned is related to NLH which means negative-low arousal-high dominance;

Fear is related to NHL which means negative-high arousal-low dominance;

Angry is related to NHH which means negative-high arousal-high dominance.

EEG activity can be observed in 5 frequency bands between approximately 0.5 Hertz and up to 30 Hertz.

Brain waves are divided into 5 categories:

a. **Beta waves (>14Hz)** are about concentration level of people. If beta power increases, emotional state arousal level will also increase.

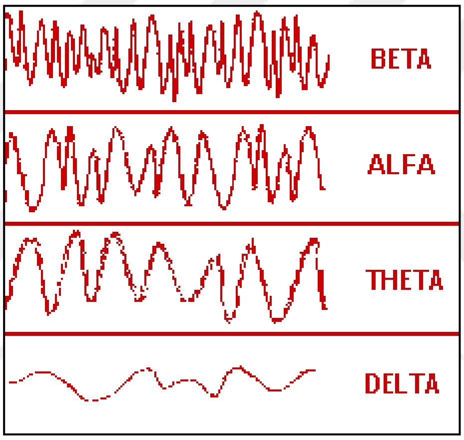
b. **Alpha waves (8-14 Hz)** corresponds to relaxation level of person and brain activities such as memory tasks and processing.

c. **Theta waves (4-8 Hz)** occur during sleep and some tasks that need mental effort and concentration.

d. **Delta waves (0.5-4 Hz)** are related to the deep sleep.

e. **Gamma waves (above 30 Hz)** are generally used for certain brain illness diagnosis (Teplan, 2002; Liu, 2012).

Figure 2.6: Samples of brain waves.



Source: M. Teplan et al., 2012

EEG recording system is consisting of;

a. Electrodes, which reads the signal coming from head surface

b. Amplifiers which provide accurate microvolt levels to be able to read and process easily.

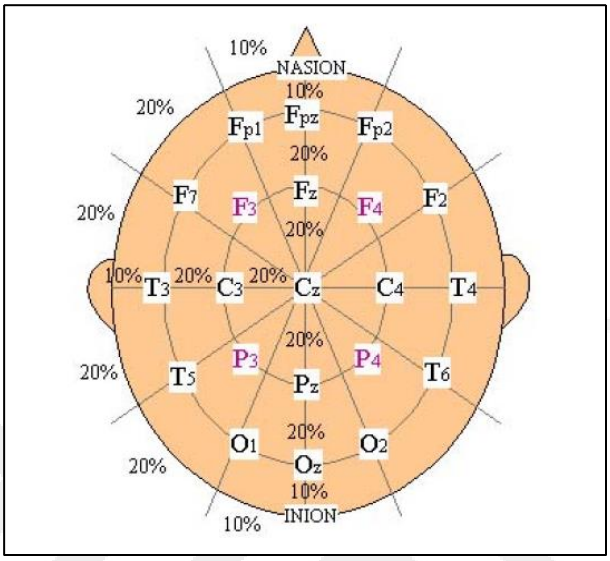
c. A/D converter, which convert the signals from analog to digital

d. Recording device, which stores and displays collected data.

EEG electrodes are essential for obtaining convenient high quality data.
In 1958, IFECN released 10-20 electrode placement system which is accepted as standard electrode placement. This system provided an illustration which shows how we should place the electrodes on the scalp. In that illustration, the skull has 3 landmarks: Nasion, preauricular points, inion and T means temporal, F means frontal, c means

central, P means posterior, and O means occipital. Odd numbers show the left side and even numbers show the right side of the head (NOMENCLATURE, 2006; Teplan, 2002; Jasper 1958).

Figure 2.7: 10-20 electrode placement system



Source: M. Teplan et al. 2012

EEG-based emotion recognition researches mainly used both with multi-channel and single-channel EEG setups when they are extracting the features to be able to classify emotions. There are some coherence and correlation analysis have been worked on in many researches for better recognition for both setups. In the following sections of this review, feature extraction methods with single-channel EEG setups will be discussed. (Conneau, 2014; Sammler, 2007).

EEG studies, focused on emotion recognition, have been examined in different experimental paradigms. Participants and stimulus type as well as presentation of stimuli could be different from each other in these studies. The international data base including emotional stimuli can be listed as follows:

DEAP

DEAP database includes signals from 32 participants. Besides these signals, it also contains face videos from 22 participants with 32 active electrodes. EMG, EOG, BVP, skin temperature, and GSR were used as peripheral nervous system physiological signals. During the music video clips, the reactions of participants were recorded simultaneously (Koelstra, S. et al., 2012).

MAHNOB

For this database, multimodal recordings from participants were recorded as a correct or incorrect stimulation marks with their active response to movies and images. The tags for all records are created according to participants' immadate response after each video or image. MAHNOB is easily reachable for academic community (Petridis, S. et al., 2013).

IAPS and IADS

The IAPS and IADS were developed to provide a set of stimuli for emotional and attentional experiments. The aim of IAPS is to develop a great set of pictures and audios which are standardized, internationally-accessible and emotionally-evocative in various categories. Pictures from IAPS and audios from IADS have been using for measuring EEG, EMG, fMRI and Heart Rate. Both databases were developed and classified by the CSEA at the University of Florida (Lang, P. et al., 2008).

POFA Pictures of Facial Affect

Paul Ekman created POFA database which includes 110 white and black photographs of facial gestures. These have been extensively used in studies about neuropsychological research (Ekman, P. et al., 1993).

The Japanese Female Facial Expression (JAFFE) Database

JAFFE database was created by M. Lyons et al in Kyushu University. This database consists of 7 facial expressions' 213 images which relates to 10 Japanese females. Each image is ranked according to 6 emotions by 60 Japanese models (Lyons, M. et al., 1998).

3. EMOTION RECOGNITION FROM EEG MEASUREMENTS

It is possible to compare the studies, presented for emotion recognition, as summarized in Appendix A.1.

The details of emotional stimulus types used in studies which were mentioned in Appendix A.1 are illustrated in Appendix A.2.

The reviewed studies which have been published in last 10 years are summarized and categorized in terms of different perspectives as shown in Appendix A.1, A.2 and A.3.

Appendix A.1 shows that Support Vector Machine (SVM) classifier has been commonly used in studies to classify the emotional states. Besides this, when the Appendix A.3 is observed, it is clearly shown that the most successful studies with their accuracies between 100percent-85percent have been achieved with SVM classifier. In the rest of the studies with accuracy rates lower than 85percent, SVM has been commonly used as well. When the Appendix A.2 is observed, it is also possible to make a comment that the mostly used stimuli types are visual-static pictures and followed by audio-visuals. The studies with the highest classification rates have used static pictures from IAPS database and also audio-visual stimulus from DEAP database.
In the following it is possible to find a comparison of the studies which achieved highest accuracies between 100percent-85percent with same classification methods and stimuli types or only same stimuli types.

Liu et al., 2015 have showed 5 min long movie clips to the participants under 30channel setup. There were 15 trial performed. FDR and SVM have been used as feature extraction and classification, respectively. Mainly, in occipital and temporal area, it was possible to observe that discriminative features were commonly founded on beta and gamma bands. The best rate was 93.31percent. Candra et al., 2015 have showed 40 music videos with 1 minute duration from DEAP database under 32channel setup, overall accuracy achieved 61.8percent by using only alpha, beta, gamma sub-bands. When 18 channel setups were used, sad emotion better observed with 88.89percent accuracy. They used SVM classification as well. Nie et al., 2011have showed 12 movie clips for 4 minutes each under 62channel setup. The average test accuracy was 87.53percent with the SVM classifier. The features were primarily on parietal and occipital lobe in alpha band, right frontal and left temporal lobe in gamma band, central site in beta band. Emotional responses of people mostly associated to high frequency bands.

Bhardwaj et al., 2015 have showed 35 pictures from IAPS for 15 sec each database under 4channel setting. The session took 20 min. Best rates were 92.5percent and 87.5percent for sad and happy emotions, respectively. SVM is outperformed the LDA in discriminating the states. Bono et al., 2016 have showed 39 face pictures twice for 850 msec. under 19 channel setting. Best accuracies were 89percent and 69percent with LDA and SVM, respectively. Segregation, integration and shape of the network features reduced the complexity of the feature extraction process for recognizing the target emotions. Yohanes et al., 2012 have performed 3 sessions with 10 pictures for each set under 2channel setting. Each picture from IAPS database was screened for 4 seconds. The best accuracy results were 84.00percent (F_{p2}) and 89.33percent (F_{p1}) related happy and sad emotions, respectively. The average was 84.67percent. ELM which is evolved from SVM provides better performance in contrast to SVM. In general, sad emotion has higher accuracy.

Aydin et al., 2016 have showed 54 pictures from IAPS as 3 blocks under 16channel setting. Each picture has been screened for 6 seconds. At all recording sites, two contrasting emotional states (pleasant, unpleasant) and three different emotional states (pleasant, neutral, unpleasant) were obtained with 100percent, 87.1percent accuracy, respectively. Multilayer perception, rotation forest and simple logistic were indicated as the best data mining classification methods. Pleasant pictures activated mostly frontal, parietal and temporal lobes. Xu et al., 2012 have performed 3 sessions with 30 trials per session under 54channel setting. Each trial had 5 images from IAPS. Each picture was shown for 2.5 seconds. The most successful approach was HOC with KNN classification method. It is reached to 90percent accuracy on distinguishing 3 classes emotions. Yoo et al., 2016 have showed 36 pictures from IAPS database with long 10 sec have been showed to the participants under 8channel setting. Best accuracies were 83percent and 74percent for joy, sadness, fear and others, respectively with the ANN classifier.

Naji et al., 2012 have used 15 music pieces from songs to each participant for 120 seconds under 6 channel setting. The overall accuracy was 86.67percent in discriminating high arousal to low, and positive valance and negative by using SVM classifier. The highest accuracy obtained from left temporalis channel with relative power, frontalis channel with relative power and SE, right temporalis channel with HOC n classifying arousal levels. When it comes to classifying valance levels, the highest results obtained from left temporalis channel with HOC, frontalis channel with relative power, right temporalis channel with relative power and HOC. Paul et al., 2015 have used audio stimuli from songs under 7channel setting. Each audio stimuli lasted in 30 sec. Best rates were 84.5percent and 82.5percent for positive and negative emotions with SVM classifier, respectively. Frontal, temporal and parietal lobes of brain were active for positive stimulus. Frontal and parietal lobes of brain were active for negative stimulus. This discrimination was effective to differentiate diseased person from healthy one. Liu et al., 2010 have used 5 songs with one minute duration under 30channel setting. 6 clips of IADS stimuli were used with one minute duration. Each clip was played twice. Higher arousal is related to higher FD values.

Murugappan et al., 2013 have used audio-visual stimuli. The audio-visual stimulus have been performed with 5 trials. The time duration of video clips were variable. KNN showed better performance with maximum mean emotion classification and lesser complexity in terms of computational method rather than PNN. Best rate was 91.33percent accuracy in beta wave with spectral entropy method. Placidi et al., 2015 have suggested specific symbols related to specific unpleasant odor to participants with 100 trials under 4channel. Each test lasted in 12 minutes. The activity was in mainly gamma band of the right hemisphere. Jie et al., 2014 have used 40 music videos from DEAP database with one minute duration under 5channel setting. The average accuracies are 80.43percent, 71.16percent for HALV-HAHV and LALV-HALV, respectively. F3, CP5, FP2, FZ and FC2 are used for recognition of high arousal; FP1, T7 and AF4 are used for negative emotions with LALV-HALV arousal. Petrantonakis et al., 2010 have used 60 pictures from POFA database twice for 5 seconds under 3channel setting. The best result from individual channel case was 77.66percent with the QDA. Liu et al., 2012 have performed 3 experiments with sound clips from IADS database under 14channel. In experiment 1, 5 sound clips with 6 seconds duration have been listened. 8 sessions have been performed. In experiment 2, one music piece with 60 seconds duration has been listened. 8 sessions have been performed. In experiment 3, 3 sound clips with 6 seconds duration have been listened. 2 sessions have been performed. Dominance level recognition algorithm computed from FC6 and FC8 electrodes in terms of being more compatible to their hypothesis using the beta/alpha ratio. The best accuracy ranged from 73.64percent to 75.17percent with SVM classifier. Torres-Valencia et al., 2014 have showed 40 music videos with 1 min long to the participants. EEG analysis with physiological signals as HR, temp, resp, etc. made possible to achieve higher discriminative information between different emotional states. Hosseini et al., 2011 have performed 8 trials with a block of 4 pictures which lasted 3 seconds under 5channel setting. For two categories, accuracy is 73.25percent with SVM. ApEn and WE are good in characterizing different emotion state. Chanel et al., 2005 have showed firstly a dark screen was shown to the participant during 3 sec for preparation. An IAPS image was shown for 6 sec. FDA over-performed Bayes classification method when classifying arousal level. Conneau et al., 2014 have performed 3 sessions with 30 blocks for each under 54channel setting.. Each blocks consisted 5 images related to a single emotional state. Standard features such as mean, standard deviation, etc. could be considered as limited in terms of not capturing sufficient information about the spectral characteristics of the signals. SCF allowed reaching 70percent accuracy as being one of spectral shape features. In the study of Katyal et al., 2014, each of 120 subjects completed 120 trials with different stimuli. Both EEG and facial results showed better percentage than individual results. Schaaff et al., 2009 have performed 2 blocks with 15 pictures under 4channel setting. Each block's duration was 20 minutes. Pleasant category is mostly rated. Kumar et al., 2015 have showed 40 music videos with 1 min long to the participants. In discrimination of features, bispectral analysis is better than power spectral features. SVM is outperformed ANN method. Filtered brain waves are better in classification accuracy than unfiltered ones. Best rates were 64.84percent for Low/High Arousal and 61.17percent for Low/High Valance. Kortelaien et al., 2015 have showed 20 video clips to the participants with 34.9-117 sec. duration. Best rates were 63.00percent and 65.1percent for valance and arousal, respectively. According to the result, it seemed that left temporal area is more informative for detection of pleasant state. In the study of Chen et al., 2016, best accuracies were 63percent for arousal and 58percent for valance. Atkinson et al., 2016 have showed 40 video clips from DEAP to the participants. The classification accuracies were 0.576 and 0.62 for valance and arousal, respectively. Wang et al., 2015 have showed 40 video clips 1 min long from DEAP to the participants. Higuchi FD showed performance with 0.0186 accuracy on valance. Atasoy et al., 2014 have showed 40 music clips to each participant. The classification accuracies were 0.576 and 0.62 for valance and arousal, respectively. Hung Liu et al., 2014 have performed 100 trials. 1 picture from IAPS has been showed per trial during 7 seconds period. IQK-SVM is more robust in classification than SVM. Average error rates are 24.90percent and 28.32 for valance and arousal, respectively. Wei et al., 2009 have showed 36 photographs of human faces. 2 blocks have been performed with 72 trials. In each trial, each face was presented twice for 2 seconds. Higher entropy founded in EEG with depression in prefrontal region. Right hemisphere disorganization in major depression is proved with WE. Wijenatre et al., 2012 have showed 40 music videos with 1 minute duration. The training could be done using a higher amount of training data. In the study of Sammler et al., 2007 musical pieces have been listened with 1 minute duration. Theta power of frontal midline is related to pleasant music. In the study of Hsu et al., 2014; a set of acoustic stimuli from IADS have been listened. For music information retrieval, emotion recognition with EEG is still promising research area.

4. RESULTS

Considering Appendix A.1, A.2 and A.3, the results can be briefly listed in form,

a. Using the correct stimuli is also important to increase the emotion effects on EEG signals. Emotional states could be clearly discriminated from each other when IAPS pictures and DEAP visual stimuli were used to evoke the states (Atkinson et al., 2016; Aydin et al., 2016; Chen et al., 2016; Yoo et al., 2016; Bhardwaj et al., 2015; Candra et al., 2015; Kumar et al., 2015; Wang et al., 2015; Wang et al., 2015; Atasoy et al., 2014; Jie et al., 2014; Liu et al., 2014; Torres-Valencia et al., 2014; Wijenatre et al., 2012; Yohanes et al., 2012; Hosseini et al., 2011; Schaaff et al., 2009; Chanel et al., 2005).

b. Based on the reviewed works, it is certain that the analyzing EEG sub-bands is much more efficient in emotion recognition rather than analyzing EEG data itself. Because technological solutions for emotion recognition have conventionally relied on assessing the activity changes in sub-bands as well as the activity differences between the hemispheres (Aydin et al., 2016; Liu et al., 2015; Placidi et al., 2015; Candra et al., 2015; Liu et al., 2012; Nie et al., 2011).

c. The studies which have used time resolution based feature extraction methods such as DWT (Discrete Wavelet Transform) are shown that it is possible to observe high accuracy in discriminating emotions rather than the studies which have used frequency resolution based methods (Aydin et al., 2016; Candra et al., 2015; Murugappan et al., 2013).

d. It is important to divide into short EEG segments of few seconds to get proper measurements due to non-stationary nature of EEG signals (Aydin et al., 2016; Liu et al., 2015; Placidi et al., 2015; Candra et al., 2015; Liu et al., 2012; Nie et al., 2011).

e. Researchers have made attempts by applying ApEn. However, ApEn has already been showed to lack relative consistency and robustness. It is biased estimation because of self-matching. The sample entropy (SampEn) statistic is, by contrast, a more robust and consistent index without self-matching. The SampEn has already been applied successfully to researches on motor imagery classification, identification of epileptic, sleep, concentration, etc (Jie et al., 2014; Murugappan et al., 2013; Naji et al., 2012).

f. The results show that the most successful emotion classification was done using Support Vector Machine (SVM) and Extreme Learning Machine (ELM). (Atkinson et al., 2016; Bono et al., 2016; Chen et al., 2016; Bhardwaj et al., 2015; Candra et al., 2015; Kumar et al., 2015; Liu et al., 2015; Paul et al., 2015; Yohanes et al., 2012).

g. Recent studies have much more focused on DWT based analysis which are used for non-stationary signal analysis. Also they allow better detection and characterization of transients by providing time-frequency localization, multiscale zooming and multiscale filtering. In some research, features such as wavelet energy, wavelet entropy, Sample Entropy (SampEn) or different wavelet functions are used for emotion recognition. The discrimination of emotions' accuracy is higher with usage of wavelet entropy and sample entropy feature extraction methods comparing the wavelet energy method in time resolution based studies (Jie et al., 2014; Katyal et al., 2014 Murugappan et al., 2013; Naji et al., 2012; Hosseini et al., 2011; Wei et al., 2009).

h. Human emotional response is mostly related to high frequency bands (Nie et al., 2011).

i. Disgust state was found to be mediated by Gamma band (Placidi et al., 2015).

j. Un-Pleasant state was to be mediated by Gamma band (Placidi et al., 2015).

k. Frontal, parietal and temporal lobes of the brain are activated by pleasant pictures (Aydin et al., 2016; Kortelaien et al., 2015; Sammler et al., 2007).

l. Sad state is more distinguishable than the other states (Yoo et al., 2016; Bhardwaj et al., 2015; Candra et al., 2015; Yohanes et al., 2012).

m. Left temporal area is more informative for detection of pleasant state (Kortelaien et al., 2015; Naji et al., 2012).

n. Right hemisphere of the brain is activated by un-pleasant state (Placidi et al., 2015; Wei et al., 2009).

5. DISCUSSION AND CONCLUSION

In this work, we reviewed the studies which have been published in recent years about recognition of emotions with single-channel EEG using different feature extraction and classification methods. Based on the reviewed works, it is certain that the analyzing EEG sub-bands is much more efficient in emotion recognition rather than analyzing EEG data itself. Because technological solutions for emotion recognition have conventionally relied on assessing the activity changes in sub-bands as well as the activity differences between the hemispheres. Besides this, the studies which have used time resolution based feature extraction methods such as DWT (Discrete Wavelet Transform) are shown that it is possible to observe high accuracy in discriminating emotions rather than the studies which have used frequency resolution based methods. FT (Fourier Transform) methods are widely used in many studies to get features from EEG signal. Because of EEG signals are none-stationary in nature, FT based methods lead the problem when analyzing them. Also FT is not able to analyze simultaneous time-frequency; because of that FT based methods are not that proper to get features from EEG. In the studies where FFT (Fast Fourier Transform) are used with Spectral Entropy (SE) to extract the feature are more successful to achieve higher accuracy in contrast to usage of Power Spectra Density.

In the view of such information, recent studies have much more focused on DWT based analysis which are used for non-stationary signal analysis. Also they allow better detection and characterization of transients by providing time-frequency localization, multiscale zooming and multiscale filtering. In some research, wavelet energy, wavelet entropy, Sample Entropy (SampEn) or different wavelet functions (such as Daubechies, Symlets, Coiflets) are used for emotion recognition. The discrimination of emotions' accuracy is higher with usage of wavelet entropy and sample entropy feature extraction methods comparing the wavelet energy method in time resolution based studies. In the other hand, usage of these methods would cause elimination of the temporal information. It is important when analyzing non-stationary signals. To achieve that in some studies, different type of wavelet functions are proposed with the higher accuracy of emotion detection especially on happy and sad emotion states. They provide that achievement by detecting transient activity in EEG signals. They are related to happy and sad emotion. Also it is important to divide into short EEG segments of few seconds to get proper measurements due to non-stationary nature of EEG signals.

In the other hand, for better detection of emotion states it is important which type of stimuli is giving to the subject to induce the emotions. Mostly used external stimuli types are visual-static pictures, audio-visual.

The results show that the most successful emotion classification was done using Support Vector Machine (SVM) and Extreme Learning Machine (ELM).

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APPENDICES

Appendix A.1: EEG analysis and classification algorithms in emotion recognition

Study	Number of recording channel	Feature extraction approach	Performance Criteria
Atkinson et al., 2016	14 Channels	Min. Redundancy-Max. Relevance (mRMR)	Support Vector Machines (SVM)
Aydin et al., 2016	16 Channels	Singular Spectrum Analysis	Data mining
Bono et al., 2016	19 Channels	Functional connectivity measures	SVM and LDA
Chen et al., 2016	Not specified	Spectral Power Density and peripheral signals	Support Vector Machines (SVM)
Yoo et al., 2016	8 Channels	Power Spectra	Artificial Neural Networks (ANN)
Bhardwaj et al., 2015	4 Channels	Power Spectral Density, energy	SVM and LDA
Candra et al., 2015	18 Channels	Wavelet Entropy	Support Vector Machines (SVM)
Kortelaien et al., 2015	32 Channels	Spectral Power (SP), Spectral Power Differences (SPD)	One-way ANOVA
Kumar et al., 2015	32 Channels	Bispectral Analysis from HOSA	Support Vector Machines (SVM)
Liu et al., 2015	30 Channels	Power Spectral Density, Fisher Discriminant Ratio	SVM
Paul et al., 2015	7 Channels	Multifractal Detrended Fluctation Analysis (MFDFA)	SVM

Placidi et al., 2015	4 Channels	Power Spectra	Classified between activation and non-activation
Wang et al., 2015	32 Channels	Higuchi Fractal Dimension	SVM
Atasoy et al., 2014	32 Channels	Higuchi Algorithm	k-NN
Conneau et al., 2014	54 Channels	Spectral Crest Factors (SCF)	Support Vector Machines (SVM)
Hsu et al., 2014	10 Channels	Spectral Centroid	ANN
Jie et al., 2014	5 Channels	SampEn (Sample Entropy)	3-fold cross-validation
Katyal et al., 2014	64 Channels	Wavelet Entropy with WPD	Artificial Neural Networks (ANN)
Liu et al., 2014	62 Channels	Spectral Powers	Imbalanced quasiconformal kernel SVM (IQK-SVM)
Torres-Valencia et al., 2014	Not specified	Intensity	Hidden Markov Models (HMM)
Murugappan et al., 2013	62 Channels	Spectral Centroid, Spectral Entropy	K Nearest Neighbor (KNN), Probabilistic Neutral Network (PNN)
Cabredo et al., 2012	23 Channels	Linear regression, C4.5	10-fold-cross-validation
Liu et al., 2012	14 Channels	Power Spectral Density	SVM
Naji et al., 2012	6 Channels	Spectral Entropy, High order crossing, relative powers	SVM
Xu et al., 2012	54 Channels	High Order Crossing (HOC)	K Nearest Neighbor (KNN)

Wijenatre et al., 2012	Neurosky mindset	Wavelet energy	ANN
Yohanes et al., 2012	2 Channels	Symlets order 6 (DWT coefficient method)	ELM, SVM
Hosseini et al., 2011	5 Channels	Approximate Entropy, Wavelet Entropy	SVM
Nie et al., 2011	62 Channels	Log band energy	SVM
Liu et al., 2010	14 Channel	Higuchi Algorithm	Fractial Dimension
Petrantonakis et al., 2010	3 Channels	High Order Crossing, Hybrid Adaptive Filtering	Quadratic discriminant analysis, k-nearest neighbor, mahalanobis database, support machine vector.
Schaaff et al., 2009	4 Channels	Cross-correlation features	SVM
Wei et al., 2009	60 Channels	Wavelet Entropy	ANOVA
Sammler et al., 2007	63 Channels	Power spectra	ANOVA
Chanel et al., 2005	64 Channels	Power spectra	FDA

Appendix A.2: Stimulus Types and International data Banks including several emotional stimuli

Stimulus Type	**Database**	**Emotional States**	**Study**
	IAPS images from	Calm, positively excited, negatively excited	Conneau et al., 2014

Visual-Static Pictures	ENTERFACE’06 Database	Positively excited, neutral, negatively excited	Xu et al., 2012
	IAPS	Pleasant, neutral, unpleasant	Aydin et al., 2016
		Joy, sadness, anger, happiness, despair and fear	Yoo et al., 2016
		Happy and sad	Bhardwaj et al., 2015
		Valance and arousal	Liu et al., 2014
		Happy and sad	Yohanes et al., 2012
		Calm-neutral, negatively excited	Hosseini et al., 2011
		Pleasant, neutral and unpleasant.	Schaaff et al., 2009
		Valance, arousal	Chanel et al., 2005
	Standardized Set of Stimuli.	Happy-positive, sad-negative, neutral.	Wei et al., 2009
Auditory (sound)	IADS	Pleasure, arousal.	Hsu et al., 2014
		Protected, satisfied, surprised, happy, sad, fear and angry	Liu et al., 2012
		Sad, pleasant, happy, anger, fear	Liu et al., 2010
		Negative, positive	Paul et al., 2015

	Songs	Arousal, valance.	Naji et al., 2012
		Joyful, sad, relaxing, stressful.	Cabredo et al., 2012
		Pleasant, unpleasant.	Sammler et al., 2007
Visual-Face Expressions, others	Face-evoked Dataset	Happy, fear and neutral	Bono et al., 2016
	Unpleasant odors	Disgust	Placidi et al., 2015
	Pictures of facial Affect (POFA)	Happiness, surprise, anger, fear, disgust, sadness.	Petrantonakis et al., 2010
Audio-visual (film-video)	DEAP	Valance, arousal	Atkinson et al., 2016
		Valance, arousal	Chen et al., 2016
		Happy, relaxed, angry, sad	Candra et al., 2015
		Valance, arousal	Kumar et al., 2015
		Valance, arousal	Wang et al., 2015
		Valance, arousal	Atasoy et al., 2014
		HAHV, LAHV, HALV, LALV	Jie et al., 2014
		Valance, arousal	Torres-Valencia et al., 2014
		Positive, negative	Wijenatre et al., 2012
	MAHNOB	Pleasant	Kortelaien et al., 2015

	International Standard Database (Not in specified)	Happy, Surprise, fear, disgust, neutral.	Murugappan et al., 2013
	JAFFE	Sad	Katyal et al., 2014
	Movies	Neutral, sad, tense, happy, disgust	Liu et al., 2015
		Positive, negative	Nie et al., 2011

Appendix A.3: Single channel EEG analysis in emotion recognition

Study	Experimental Paradigm	EEG analysis method	Classification performance	Main results
Aydin et al., 2016	54 pictures from IAPS have been showed as 3 blocks. Each picture has been screened for 6 seconds.	SSA	100%-87.1%	At all recording sites, two contrasting emotional states (pleasant, unpleasant) and three different emotional states (pleasant, neutral, unpleasant) were obtained with 100%, 87.1% accuracy, respectively. Multilayer perception, rotation forest and simple logistic were indicated as the best data mining classification methods. Pleasant pictures activated mostly frontal, parietal and temporal lobes.
Liu et al., 2015	Movie clips long 5 min have been showed to the participants. There were 15 trial performed.	PSD	93.31%	FDR was good in increasing the discriminative power of features. Mainly, in occipital and temporal area, it was possible to observe that discriminative features were commonly founded on beta and

				gamma bands.
Bhardwaj et al., 2015	35 pictures have been showed for 15 sec each. The session took 20 min.	PSD and energy	92.5%and 87.5%	Best rates were 92.5% and 87.5% for sad and happy emotions, respectively. SVM is outperformed the LDA in discriminating the states.
Murugappan et al., 2013	The audio-visual stimulus have been performed with 5 trials. The time duration of video clips were variable.	SE	91.33% with K=2	KNN showed better performance with maximum mean emotion classification and lesser complexity in terms of computational method rather than PNN. Best rate was 91.33% accuracy in beta wave with spectral entropy method.
Placidi et al., 2015	Specific symbols related to specific unpleasant odor have been showed to participants with 100 trials. Each test lasted in 12 minutes.	PS	About 90%	The activity was in mainly gamma band of the right hemisphere.
Xu et al., 2012	3 sessions have been performed with 30 trials per session. Each trial had 5 images from IAPS. Each picture was shown for 2.5 seconds.	HOC	90%	The most successful approach was HOC with KNN classification method. It is reached to 90% accuracy on distinguishing 3 classes emotions.
Bono et al., 2016	39 face pictures have been screened twice for 850 msec.	Functional connectivity measures	89% and 69%	Best accuracies were 89% and 69%with LDA and SVM, respectively. Segregation, integration and shape of the network features reduced the complexity of the feature extraction process for

				recognizing the target emotions.
Candra et al., 2015	40 music videos have been shown with 1 minute duration.	Wavelet Entropy	88.89%	Under 32 channel setup, overall accuracy achieved 61.8% by using only alpha, beta, gamma sub-bands. When 18 channel setups were used, sad emotion better observed with 88.89% accuracy.
Nie et al., 2011	12 movie clips have been showed for 4 minutes each.	Log band energy	87.53%	The average test accuracy was 87.53%. The features were primarily on parietal and occipital lobe in alpha band, right frontal and left temporal lobe in gamma band, central site in beta band. Emotional responses of people mostly associated to high frequency bands.
Naji et al., 2012	15 music pieces have been listened to each participant for 120 seconds.	SE, HOC, RP	86.67%	The overall accuracy was 86.67% in discriminating high arousal to low, and positive valance and negative by using SVM classifier. The highest accuracy obtained from left temporalis channel with relative power, frontalis channel with relative power and SE, right temporalis channel with HOC n classifying arousal levels. When it comes to classifying valance levels, the highest results obtained from left temporalis channel with HOC, frontalis channel with relative power, right temporalis channel with relative power and HOC.

Liu et al., 2010	5 songs were used with one minute duration. 6 clips of IADS stimuli were used with one minute duration. Each clip was played twice.	FD	84.9%	Higher arousal is related to higher FD values.
Yohanes et al., 2012	3 sessions have been performed with 10 pictures for each set. Each picture was screened for 4 seconds.	Symlet order 6 (DWT coefficient method)	84.67%	The best accuracy results were 84.00% (F_{p2}) and 89.33% (F_{p1}) related happy and sad emotions, respectively. The average was 84.67%. ELM provides better performance in contrast to SVM. In general, sad emotion has higher accuracy.
Paul et al., 2015	Each audio stimuli lasted in 30 sec.	MFDFA	84.5% and 82.5%	Best rates were 84.5% and 82.5% for positive and negative emotions with SVM classifier, respectively. Frontal, temporal and parietal lobes of brain were active for positive stimulus. Brain's parietal and frontal lobes were active for negative stimulus. In order to distinguish diseased person from healthy one that discrimination was effective.
Yoo et al., 2016	36 pictures with long 10 sec have been showed to the participants.	Power Spectra	83%, 74%	Best accuracies were 83%and 74% for joy, sadness, fear and others, respectively.
Jie et al., 2014	40 music videos have been watched with one minute duration.	SampEn	80.43%, 71.16%	The average accuracies are 80.43%, 71.16% for HALV-HAHV and LALV-HALV, respectively. F3, CP5, FP2, FZ and FC2 are used for recognition of high arousal; FP1, T7 and AF4 are used for negative emotions

				with LALV-HALV arousal.
Petrantonakis et al., 2010	60 pictures have been showed twice for 5 seconds.	HAF-HOC	77.66%	The best result from individual channel case was 77.66% with the QDA.
Liu et al., 2012	3 experiments have been performed with sound clips from IADS database. In experiment 1, 5 sound clips with 6 seconds duration have been listened. 8 sessions have been performed. In experiment 2, one music piece with 60 seconds duration have been listened. 8 sessions have been performed. In experiment 3, 3 sound clips with 6 seconds duration have been listened. 2 sessions have been performed.	SPD	73.64%-75.17%	Dominance level recognition algorithm computed from FC6 and FC8 electrodes in terms of being more compatible to their hypothesis using the beta/alpha ratio. The best accuracy ranged from 73.64% to 75.17% with SVM classifier.
Torres-Valencia et al., 2014	40 music videos with 1 min long have been listened to the participants.	HMM	75%	EEG analysis with physiological signals as HR, temp, resp, etc. made possible to achieve a higher discriminative information between different emotional states.
	8 trials have been performed with a block			For two categories, accuracy is 73.25% with SVM. ApEn and

Hosseini et al., 2011	of 4 pictures which lasted 3 seconds.	ApEn, WE	73.25%	WE are good in characterizing different emotion state.
Chanel et al., 2005	Firstly a dark screen was shown to the participant during 3 sec for preparation. An IAPS image was shown for 6 sec.	Power spectra	70%	FDA over-performed Bayes classification method when classifying arousal level.
Conneau et al., 2014	3 sessions have been performed with 30 blocks for each. Each blocks consisted 5 images related to a single emotional state.	SCF	70%	Standard features such as mean, standard deviation, etc. could be considered as limited in terms of not capturing sufficient Information about the spectral characteristics of the signals. SCF allowed reaching 70% accuracy as being one of spectral shape features.
Katyal et al., 2014	Each of 120 subjects completed 120 trials with different stimuli.	WE	70%	Together EEG and facial results showed better percentage than individual results.
Schaaff et al., 2009	2 blocks with 15 pictures have been showed. Each block's duration was 20 minutes.	Cross-Correlation	66.67%	Pleasant category is mostly rated.
Kumar et al., 2015	40 music videos with 1 min long have been listened to the participants.	Bispectral Analysis	64.84%and 61.17%	In discrimination of features, bispectral analysis is better than power spectral features. SVM is outperformed ANN method. Filtered brain waves are better in classification accuracy than unfiltered ones. Best rates were 64.84% for Low/High Arousal and 61.17% for Low/High

				Valance.
Kortelaien et al., 2015	20 video clips have been shown to the participants with 34.9-117 sec. duration.	SPD	63.00% and 65.1% with P<0.05	Best rates were 63.00% and 65.1% for valance and arousal, respectively. According to the result, it seemed that left temporal area is more informative for detection of pleasant state.
Chen et al., 2016	Not Specified	Power spectral density and peripheral signals	63% and 58%	Best accuracies were 63% for arousal and 58% for valance.
Atkinson et al., 2016	40 video clips from DEAP have been showed to the participants.	mRMR	60.72% and 62.4%	Best accuracy rates were 60.72% and 62.4% for arousal and valance, respectively.
Wang et al., 2015	40 video clips 1 min long from DEAP have been showed to the participants.	Higuchi FD	0.0186	Higuchi FD showed performance with 0.0186 accuracy on valance.
Atasoy et al., 2014	40 music clips have been showed to each participant.	Higuchi Algorithm	0.576-0.62	The classification accuracies were 0.576 and 0.62 for valance and arousal, respectively.
Hung Liu et al., 2014	100 trials have been performed. 1 picture from IAPS has been showed per trial during 7 seconds period.	SP	24.90% - 28.32%	IQK-SVM is more robust in classification than SVM. Average error rates are 24.90% and 28.32% for valance and arousal, respectively.

Wei et al., 2009	36 photographs of human faces have been showed. 2 blocks have been performed with 72 trials. In each trial, each face was presented twice for 2 seconds.	Wavelet Entropy (WE)	F(2,30)=4.67, P=0.013	Higher entropy founded in EEG with depression in prefrontal region. Right hemisphere disorganization in major depression is proved with WE.
Wijenatre et al., 2012	40 music videos have been showed with 1 minute duration.	Wavelet energy	High accuracy	The training could be done using a higher amount of training data.
Sammler et al., 2007	Musical pieces have been listened with 1 minute duration.	Power spectra	P<.01	Theta power of frontal midline is related to pleasant music.
Hsu et al., 2014	A set of acoustic stimuli from IADS have been listened.	SC	Not included	For music information retrieval, emotion recognition with EEG is still promising research area.