THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

REVIEW ON BRAIN CONNECTIVITY MEASUREMENTS USED FOR EMOTION RECOGNITION

Master's Thesis

FEHMI VOLKAN ÖZDEMIR

ISTANBUL, 2016

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ABSTRACT

REVIEW ON BRAIN CONNECTIVIY MEASUREMENTS USED FOR EMOTION RECOGNITION

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Bioengineering Program

Thesis Supervisor: Assoc. Prof. Dr. Serap AYDIN

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The brain is the main control unit which provides the autonomous internal balance of body functions. Electrical brain activities so called Electro-Encephalo-Graphy (EEG) has been analyzed for detection of both neuro-physiological and psychological as well as anatomical abnormalities by using computer based advanced signal processing tools. Nowadays, emotion recognition is becoming more and more popular research topic in a wide range of field from neuroscience to neuro-marketing. Emotional states, which have been evoked in response to affective stimuli approved internationally, have been detected with respect to descriptive parameters as follows; facial expressions, neuro-imaging brain slices, physiological factors such as heart-rate and electrical tissue conductivity and, EEG series. However, EEG is found to be most effective and robust tool for emotional states. In the frame of EEG analysis, connectivity and dependency measurements, which refers the level of inter-hemispheric synchronic behaviors between right and left hemispheres, and single-channel EEG analysis have been examined for emotion recognition. In this study, brain connectivity measurements and hemispheric dependency measurements have been summarized in comparison to each other to state the best recognizer depending on experimental paradigm and classifier specifications.

Key Words: EEG, Brain Connectivity, Emotion Recognition, Classification

ÖZET

DUYGU TANIMLAMA İÇİN KULLANILAN BEYİN BAĞLANTILARI ÖLÇÜMLERİ ÜZERİNE DERLEME

Fehmi Volkan ÖZDEMİR

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Beyin tüm vücut fonksiyonlarının otonom iç dengesini sağlayan ana kontrol birimidir. EEG adı verilen elektriksel beyin aktiviteleri, nörofizyolojik, psikolojik ve anatomik anormalliklerin tespiti için bilgisayar tabanlı ileri sinyal işleme araçları kullanılarak analiz edilmektedir. Günümüzde gittikçe popülerleşmekte olan duygu durumu tanıma başlığı, sinirbilimden nöro-markete kadar geniş bir alanı ilgilendirmektedir. Uluslar-arası ölçütlerde geçerliliği onaylanmış veri-tabanlarında yer alan duygulanım uyaranları ile oluşturulan duygu durumlarını tanımada; yüz ifadelerinin fotoğrafları, dilimsel beyin görüntüleri, kalp atış oranı ve elektriksel deri direnç seviyesi gibi fizyolojik parametreler ve EEG sinyalleri kullanılan tanımlayıcı parametrelerdir. Bu parametreler arasında en güvenilir ve duygu durumunu karakterize edebilen ise EEG sinyalleridir. Ancak, literatürde EEG analizleri, duygu durumu tespitinde en sağlam ve elverişli araçlar olarak bulunmuştur. Duygu tanıma amaçlı EEG analizlerinde ise tek-kanal EEG analizlerinin yanısıra; sağ ve sol hemisfer-arası senkronik haberleşme düzeyini ölçen bağıllık ve bağlantısallık ölçütleri ele alınmaktadır. Bu çalışmada; sınıflandırıcı özellikleri ile deney paradigmasına bağlı olarak en iyi duygu durum tanıma yaklaşımını saptamak için hemisferik bağıllık ve bağlantısallık kestirim yöntemleri, birbirleri ile kıyaslanarak özetlenmiştir.

Anahtar Kelimeler: EEG, Beyin Bağlantıları, Duygu Tanıma, Duygu Sınıflandırma

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ABBREVIATIONS

ANN	:	Artificial Neural Network
BN	:	Bayesian Network
CC	:	Cross Correlation
CFS	:	Correlation-based Feature Selection
CV	:	Cross Validation
DWT	:	Discrete Wavelet Transform
EEG	:	Electroencephalogram
ENN	:	Extended Nearest Neighbor
EOG	:	Electro-oculogram
FCM	:	Fuzzy C Means
FFT	:	Fast Fourier Transform
FKM	:	Fuzzy K Means
GA	:	Genetic Algorithm
IADS	:	International Affective Digitized Sound System
IAPS	:	International Affective Picture System
KNN	:	K – Nearest Neighbor (KNN)
LDA	:	Linear Discriminant Analysis
QDA	:	Quadratic Discriminant Analysis
RBF	:	Radial Basis Function
SL	:	Surface Laplacian
SVM	:	Support Vector Machine
PCA	:	Principal Component Analysis
LCV	:	Leave-one out cross-validation

1. INTRODUCTION

In this thesis, it is aimed to define emotion recognition by analyzing EEG signals. Also, scientific studies are compiled and summarized analogically.

Emotion can be defined as group of reactions/feelings to the encountered events (Ekman 1999). It is studied from different angles like examining facial expressions with photograph analysis, examining facial muscles and brain signals by recording and examining homodynamic changes such blood pressure, heart beat ratio, respiration volume to determine the emotion status of people. However, the most common way is analyzing electrical brain activities which change depending on direct emotion status and categorizing them according to stimuli. In these studies; stimuli type which is used during measurement of EEG signals, EEG analyses approach and applied classifier type differ.

This thesis work is compilation/composition to determine the most appropriate affection stimuli type, experiment paradigm and classifier type. Objectives are listed below in detail.

1.1 GOAL OF THE THESIS

The main aims of this thesis are listed below:

i. Review of literature based on EEG-Based Emotion Recognition and Comparing other studies in this field with respect to
   - i.1. EEG recording set-ups
   - i.2. Feature extraction methods
   - i.3. Classification Algorithms

ii. Defining most important parameters to have better classification performance in terms of
   - ii.1. Stimulus type
   - ii.2. Repetition of emotional stimulus
   - ii.3. Inter-trial-inter duration
   - ii.4. Experimental time
   - ii.5. Sampling frequency

ii.6. Performance criteria

ii.7. Number of measurement electrodes

iii. Finding best stimulus and database types

iv. Finding features that gives higher accuracies

v. Finding and proposing best classification methods

vi. Compounding best experiment methods to have more successful studies

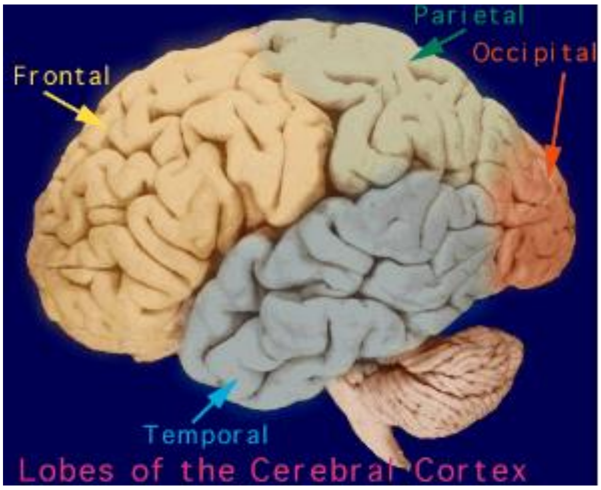
1.2 EEG

The nervous system is divided into CNS (Central Nervous System) and PNS (Peripheral Nervous System) which controls our daily life decision. The Brain gives its directions to the body via nervous system. It is split into three parts:

- The Forebrain which includes thalamus, hypothalamus and cerebrum,
- Midbrain which includes the tegmentum and tectum,
- Hindbrain which includes the medulla, pons and cerebellum.

The biggest part of the human brain is the cerebrum that is related with brain functions like action and thought. As seen in Figure 1-1, it is split into lobes called the parietal, occipital, temporal and frontal (Patricia 2000).

Figure 1-1: Lobes of the cerebral cortex



Source: http://serendip.brynmawr.edu/bb/kinser/Structure1.html

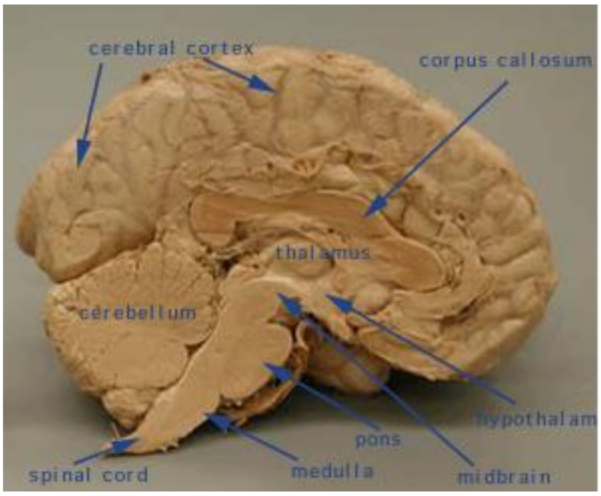
Each lobe is associated with a task as following;

- Frontal Lobe: reasoning, planning, parts of speech, movement, emotions, and problem solving
- Parietal Lobe: associated with movement, orientation, recognition, perception of stimuli
- Occipital Lobe: associated with visual processing
- Temporal Lobe: associated with perception and recognition of auditory stimuli, memory, and speech

The structure which is responsible of coordination of movement, balance and posture is the cerebellum.

The other system is limbic system which contains the amygdala, hypothalamus, hippocampus and thalamus (see Figure 1-2). Those parts of the brain are related to emotional states of a human (Patricia 2000).

Figure 1-2: Mid-saggital view of the brain



Source: http://serendip.brynmawr.edu/bb/kinser/Structure1.html

a. **Amygdala:** Amygdala is a large part and located right under the surface of the mid-front part of the temporal lobe. It involves in memory, emotion, and fear. It is a part of the limbic system.

b. **Thalamus**: Thalamus consists of gray matter and located in deep of forebrain at the top of the diencephalon. It has sensory and motor functions where most of sensory information from neurons enters into this structure. Before information reaches to the cortex, axons from every sensory system synapse in thalamus as the last relay site.

c. **Hypothalamus:** Hypothalamus is located onto thalamus as a part of the diencephalon. It is responsible for emotions, hunger, thirst, homeostasis, circadian rhythms, pituitary and control of the autonomic nervous system.

d. **Hippocampus:** Hippocampus is the part of the cerebral hemisphere located in basal medial part of the temporal lobe. It is responsible for short-term memory, permanent-memory and learning.

EEG, PET and fMRI are some of the several methods to measure brain activity, but researchers will focus on the EEG signal and its frequency analysis for emotion recognition (Hosseini et al. 2011). It is known that limbic system is mainly responsible for emotional progress in humans.

EEG (Electroencephalography) is an activity which is divided into 5 different frequencies with the scale between 0.5-30 Hz (Jasper 1958). The EEG usage is increasing due to its higher temporal resolution whereas MRI and CT could not provide it (Teplan 2002).

a. Beta waves (>14Hz)
b. Alpha waves (8-14 Hz)
c. Theta waves (4-8 Hz)
d. Delta waves (0.5-4 Hz)
e. Gamma waves (above 30 Hz)

Electroencephalography (EEG) is a monitoring method in order to record electrical activity of the brain (Jeffrey et al., 2011). The EEG (Electroencephalography) consists of electrical activities of neurons that have intrinsic electrical properties. Neurons produce electrical and magnetic fields and can be recorded by electrodes at a short distance from the sources or from the cortical surface, or at longer distances with non-invasive easy ways (Mulert et al., 2010).

These signals that come from brain have low amplitude and it is hard to reach these clinically needed information. The research topic of identifying connectivity within and between brain areas has a growing interest. Since early 1960s, accurately quantifying brain connectivity is a challenging problem (Sakkalis 2011).

EEG measurements are often used in diagnosing neurophysiologic and neuropsychological diseases. ‘Emotion Recognition’ however is an application area/field which shows EEG analyses are superior than neuroimaging approaches and it is getting more popular each day.

There are two ways to analyze EEG signals. The first is analyzing each measurement channel one by one. Second one is the analysis of synchronization between two channels which expresses the correlation between symmetrical brain areas.

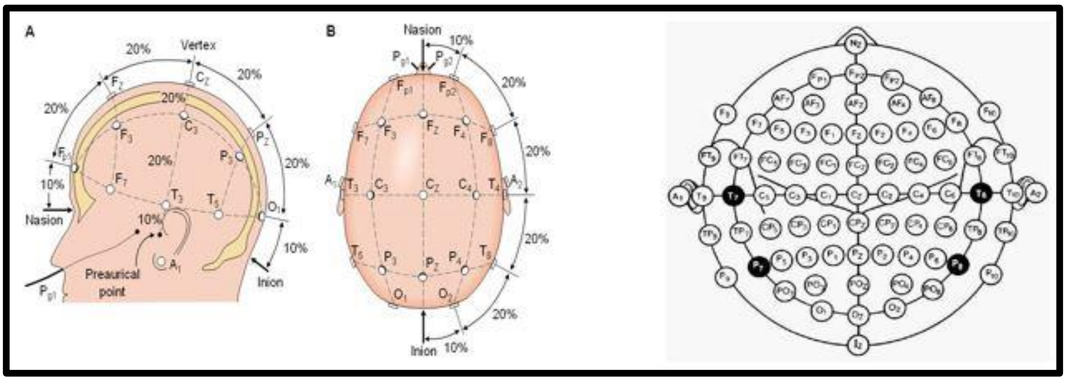
Methods that are used in single-channel EEG analyses are; wavelet transform, fourier transform, short-time fourier transform, entropy estimation, power spectral density estimation, principle component analysis, empirical mode decomposition, dimensional complexity, Lyapnov Exponents, Hurst exponents, fractal dimension approaches (Wendling et al. 2009, Thatcher 2010, Sakkalis 2011, Yuvaraj et al. 2014).

Physiological signal (both central and nervous systems) analysis is a possible approach for emotion recognition and categorizing emotional states based-on EEG features via neural networks has investigated for years (Lahane et al. 2015, Murugappan et al. 2010).

Brain connectivity began to be used cross-correlation of pairs of EEG signals in the 1960s. Researches and interests for EEG analyze for functional brain connectivity that reconstructed from scalp signals was increased in the recent past years (Yuvaraj et al. 2014).

There are three main regions of the human brains; brain stem, cerebellum and cerebrum. In order to measure these electrical quantities, electrodes must be positioned on these three regions with 10-20 or 10-10 international electrode position rule (Figure 1.3)

Figure 1-3: International 10-20 system and International 10-10 system



Source:http://www.bem.fi/book/13/fi/1302a.gif , http://www.brainmaster.com/kb_upload/10-10.jpg

Although there are many advances both on recording and analysis of EEG signals, researchers are trying to find the optimal way to process data to identify brain networks. For EEG signal analysis, data acquisition, pre-processing, feature extraction with wavelet transform, and emotion classification techniques must be discussed.

1.3 BRAIN CONNECTIVITY

Analysis of brain connectivity can be introduced in both conceptual and practical senses: Conceptually, functional segregation is concerned for brain mapping in past

(Friston 2011). However, in last decade, research studies including ‘‘Brain Connectivity’’ have been published instead of the works looking at functional segregation (PubMed.gov. U.S. National Library of Medicine). This spread from functional segregation to integration (brain connectivity) can be explained by close relationship between functional and effective connectivity of the brain although the existence of distinction on both procedural and statistical analysis tools (Friston et al. 1995, Friston 2005). From a historical point of view, this distinction causes the investigation of regional brain lobes and their specified functions in neuro-imaging studies such that different brain functions can be organized by a neural population in particular region of the brain. Although, this phrenology was not accepted by scientists Stam et al. (1995), during the following decades, the same phrenology was tested on animals. Further, clinicians concluded that it was difficult to associate a specific function with a particular brain region due to anatomical connections between brain lobes.

In neuro-imaging field, both functional segregation and integration of segregated areas have proven more difficult to assess. The integration was characterized by functional connectivity, which defines the correlations among electrophysiological measurements, while functional connectivity was defined as statistical dependencies among several time varying neuro-physiological events. In fact, such correlations can be estimated in different domains by using various methods depending on both experimental paradigm and goal in diagnose (Gerstein et al.,1969).

The other connectivity term, effective connectivity can be defined as time dependent population level explicitly to the influence generated by a neural system over another (Aertsen et al.,1991). The origin of effective connectivity is single-unit electrophysiology (Gerstein et al.,1969).

Functional connectivity is an observable phenomenon that can be quantified with measures of statistical dependencies, such as cross-correlations, coherence, mutual information, transfer entropy, etc. In contrast to functional connectivity, effective connectivity can be measured by parameters with respect to a model. In other words, effective connectivity corresponds to coupling, while functional connectivity corresponds connectivity. Therefore, the procedure of effective connectivity depending on model assumption is very different from that of functional connectivity depending on probability density functions. In summary, it can be said that functional connectivity does not provide any inference about the coupling between two brain lobes. Conventionally, functional connectivity is measured by using correlation coefficients and frequency domain coherence functions.

Brain connectivity measures can be used to estimate interactions between brain regions from electrophysiological data. Coherence, correlation and other related measured signals have been widely used to estimate functional connectivity (Wendling et al. 2009). In order to measure spatial correlations between different bands, coherence can be used (Sakkalis 2011). To find correlation between the emotional changes and Electroencephalogram(EEG) signals, researchers have been trying several approaches that can be seen in the studies of Thatcher (2010) and Hosseini et al (2011).

Coherence is widely used for signal processing, and other methods are based on Probability Density Function to assess entropy or mutual information (Hosseini et al. 2011, Wendling et al. 2009).

Although these techniques can be used in order to identify brain networks in normal brain functions such as memory, learning, emotions or behavior adaptation to stimuli, they can also be used in neurological disorders like epilepsy, autism or schizophrenia (Yuvaraj et al. 2014).

In addition to emotion recognition systems, these methods can be used for neural diseases such as dementia, PD (Parkinson’s Disease), seizures etc. For instance; Pearson’s correlations are used for coherence values of electrode pairs recorded in emotional states such as happy, sad, anger, surprise, fear and disgust and coefficients can be differed in frequency bands of EEG. These coherence values increase in dementia (Leuchter et al. 1993), AIDS (Newton et al. 1994), and mild head injury (Thatcher 2010). However, in Alzheimer’s disease (Leuchter et al. 1993), Parkinson’s Disease and depression, decreases in coherence can be seen because of their decreased functional correlations of two regions.

There are new studies to find the correlation between different emotions and EEG signals, thanks to the success in analysis methods and brain computer interface systems.

Biological signals also contain noise besides useful information. Therefore, it is better to transform the raw data to obtain a better input for classification processes.

There are many works with cross-correlation (CC) function in time-domain (Barlow 1954, Braizer et al. 1952), but after Fast Fourier Transform (FFT) algorithms were introduced, signal processing was transformed into the frequency domain (Lee et al. 2006), and coherence function was begun to be used (Cooley 1962). In addition to the Fourier transform (or STFT), the wavelet and Hilbert transform, and complex demodulation are the other methods for studying EEG activity in frequency domain. They divide the methods into two main categories. The first category includes cross-correlation or coherence function (linear methods). The second category has nonlinear regression, generalized synchronization and phase synchronization.

Cross-correlation is one of the most classical measure type of interdependence between two-time series. Higher correlations show stronger functional relationships between the related brain regions. In contrary, Mutual Information (MI) computes the statistical dependence between time series of physiological data. Phase Synchronization (PS) is a method that detect the phase locking values between two systems (Yuvaraj 2014, Kim et al 2013).

1.4 EEG SYNCHRONIZATION

One of the most important relationship features between EEG signals of different brain areas is EEG synchronization (Fell et al., 2001). ‘Synchronization’ term in EEG-related fields generally refers to phase-based relations of different brain regions or advanced EEG power in one region. There are many methods that estimates synchronization of multiple time series in the group of Phase Synchronization and Generalized Synchronization Indexes that are explained below (Fell et al, 2011).

1.4.1 Estimation of EEG Correlations

In order to estimate EEG correlations, Pearson’s Correlation Coefficient, Cross-correlation function, coherence analysis and phase slope index can be used as classical measurement techniques.

a) Pearson's correlation coefficient (COR)

Pearson's correlation coefficient method is generally used for derivation of optimal filters for noise reduction. In addition, researchers are using it especially for analyzing those optimal filters with respect to their performances. PCC shows dependency and correlation between two variables or vectors and it is defined as:

$$R_{xy} = \frac{1}{N}\sum_{k=1}^{N} x(k)y(k) \tag{1.1}$$

where $-1 \leq R_{xy} \leq 1$

b) Cross-correlation function (XCOR)

Cross-correlation function is generally used to compare two functions by means of similarities. By this way, correlation degree of multiple series can be calculated with the formula below:

$$C_{xy}(\tau) = \frac{1}{N-\tau}\sum_{k=1}^{N-\tau} x(k+\tau)y(k) \tag{1.2}$$

where $-1 \leq C_{xy}(\tau) \leq 1$.

c) Coherence Analysis (COH)

Coherence is generally used for defining similarity of two signals such as x(t) and y(t). For EEG analysis, coherence can be used to quantify functional connectivity between different brain regions. Many researchers have been using coherence to investigate emotional states with different emotional stimulus (Yuvaraj et al, 2015). It is the squared module of the coherency function (K), which is the ratio between the cross power spectral density, $S_{xy}(f)$, between x(t) and y(t), and their individual power spectral densities $S_{xx}(f)$ and $S_{yy}(f)$:

$$K_{xy}(f) = \frac{S_{xy}(\mathrm{f})}{\sqrt{S_{xx}(f)S_{yy}(\mathrm{f})}} \tag{1.3}$$

Thus, the coherence can be defined as below:

$$COH_{xy} = k_{xy}^{2}(f) = |K_{xy}(f)|^{2} = \frac{|S_{xy}(f)|2}{S_{xx}(f)S_{yy}(f)} \tag{1.4}$$

where $0 \leq COH_{xy}(f) \leq 1$ at frequency f.

d) Phase Slope Index (PSI)

Nolte et al, (2008) said that correct interactions between neural signals of two signals x(t) and y(t) recorded from two sensors happen with a certain time delay. They defined the PSI between x(t) and y(t) as:

$$PSI = \upsilon_{xy} = \frac{\acute{\upsilon}_{xy}}{std\ (\acute{\upsilon}_{xy})} \tag{1.5}$$

where values of PSI > 2.

1.4.2 Estimation of EEG Synchronization in Phase Between Two Lobes

Five main methods can be used for Phase Synchronization Connectiviy which are explained below (Niso et al, 2013):

a) Phase Locking Value (PLV)

In 1999, Lachaux et al proposed PLV method to precisely detect frequency range between two brain regions. They use three steps:

i. applying band-pass filter
ii. Computing convolution with Gabor wavelet transform
iii. Testing phase-difference samples with Raleigh Test method.

After those 3 steps, they defined the PLV as:

$$PLV = |\frac{1}{N}| \sum_{n=1}^{N} e^{i\Delta\Phi ref(tn)}| \tag{1.6}$$

$$= \sqrt{\cos \Delta\Phi_{rel}(t)^2 + \sin \Delta\Phi_{rel}(t)^2} \tag{1.7}$$

where $0 \leq$ PLV ≤ 1.

b) Phase-Lag Index (PLI)

PLI is proposed in order to measure phase synchronization of two signals. PLI is generally used for bio-signal processing. Stam et al. (2007) showed the PLI as a measurement of phase synchronization for the asymmetry of the phase difference distribution between two signals and it is defined as:

$$PLI = |\frac{1}{N}| \sum_{n=1}^{N} sign(\Delta\Phi_{rel}(t_n))| \tag{1.8}$$

where $0 \leq$ PLI ≤ 1.

$\Delta\Phi(t) = |\Phi_x(t) - \Phi_y(t)| \leq cte$ and $\Delta\Phi_{rel}(t) = \Delta\Phi\ (t) mod 2\Pi$ (1.9)

c) Weighted Phase-Lag Index (WPLI)

Researchers had problems with PLI about detection of correct changes in PS. Then, they decided to extend the PLI by weighting the phase lags and leads with magnitude of the imaginary component of cross-spectrum (Vinck et al, 2011). This new method which can detect small changes in phase synchronization is called as Weighted Phase-Lag Index. WPLI weights sign($\Im$(X)) by |$\Im$(X)|, where $\Im$(X) is the imaginary component of the cross-spectrum between x(t) and y(t):

$$WPLI = \frac{|\langle \Im(X) \rangle|}{\langle |\Im(X)| \rangle} = \frac{|\langle |\Im(X)| sign(\Im(X)) \rangle|}{\langle |\Im(X)| \rangle} \qquad (1.10)$$

where $0 \leq WPLI \leq 1$

d) rho index (RHO)

Rho index method is based Shannon's entropy (Shannon et al., 1949). It is defined as:

$\rho = (S_{max}-S)/S_{max}$ where S_{max} is the maximal entropy (that of uniform distribution),

$$S = -\sum_{k=1}^{N} p_k \ln(p_k) \qquad (1.11)$$

where p_k is the probability of $\Delta\ \phi_{rel}(t)$ in the k-th bin and $0 \leq \rho \leq 1$, (Tass et al. 1998).

e) Directionality Phase Index (DPI)

i. Evolution Map Approach (EMA)

From c_x^2 and cy^2, directionality of PS can be calculated as:

$$d^{xy} = \frac{c_x - c_y}{c_x + c_y} \qquad (1.12)$$

Where $-1 \leq d^{xy} \leq 1$ (Rosenblum et al, 2002).

ii. Instantaneous Period Approach (IPA)

$$T_x(k) = T_x^0(k) + \O_x(\Phi_x(t_k),\Phi_y(t_k)) + \eta_x\ (t_k) \qquad (1.13)$$

where T_x^0 (k) is mean period of x(t), and η_x (t_k) is the noise component of phase increment.

$$d^{xy} = \frac{c_x - c_y}{c_x + c_y} \qquad (1.14)$$

where $-1 \leq r^{xy} \leq 1$ (Rosenblum et al. 2001).

1.4.3 Estimation of EEG Synchronization Over Whole Cortex

a) **S Index**

$$S^{(k)}(X|Y) = \frac{1}{N}\sum_{n=1}^{N}\frac{R_n^k(X)}{R_n^k(X|Y)} \tag{1.15}$$

where $0 < S(X|Y) \leq 1$ (Arnold 1999).

b) **H Index**

$$H^{(k)}(X|Y) = \frac{1}{N}\sum_{n=1}^{N}\frac{\log(R_n(X))}{R_n^k(X|Y)} \tag{1.16}$$

where $0 < H(X|Y) < \infty$. We can say that if X & Y are independent, it will be 0 (Arnold 1999).

c) **N Index**

$$N^{(k)}(X|Y) = \frac{1}{N}\sum_{n=1}^{N}\frac{R_n(X)-R_n^k(X|Y)}{R_n(X)} \tag{1.17}$$

where $0 \leq N(X|Y) < 1$. If range is close to 0, X & Y will be independent and if it is close to 1, it means they are synchronized (Quiroga et al. 2002).

d) **M Index**

$$M^{(k)}(X|Y) = \frac{1}{N}\sum_{n=1}^{N}\frac{R_n(X)-R_n^k(X|Y)}{R_n(X)-R_n^k(X)} \tag{1.18}$$

where $0 \leq M(X|Y) \leq 1$. If range is close to 0, X & Y will be independent like in N index above, and if it is close to 1, it means they are fully synchronized (Quiroga et al. 2002).

e) **L Index**

$$L^{(k)}(X|Y) = \frac{1}{N}\sum_{n=1}^{N}\frac{G_n(X)-G_n^k(X|Y)}{G_n(X)-G_n^k(X)} \tag{1.19}$$

Average rank is $G_n(X) = N/2$ and minimized average rank is $G_n^{(k)}(X) = (k+1)/2$

where $0 \leq L(X|Y) \leq 1$. When range is close to 0; X & Y will be independent and when it is close to 1; it means they are synchronized like N index (Andrzejak et al, 2009).

f) Synchronization Likelihood (SL)

Stam et al. (2002), have defined SL as most popular index to predict Generalized Synchronizations which is related to generalized mutual information. Unlike other GS indexes, SL is a multivariate system which gives dynamical interdependencies. For this reason, it is defined as below in their study:

$$SL_{m,n} = \frac{1}{2(w_2 - w_1)} \sum_{j=1}^{N} S_{m,n,j} \tag{1.20}$$

where $w_1 < |n-j| < w_2$.

1.4.4 Estimation of EEG Causality Coherence

a) Clasical Linear Granger Causality (GC)

Nobel Prized researcher Clive Granger formulated the concept of causality which can be defined as: If one of the simultaneously obtained x(t) and y(t) signals can influence and estimate the other one by adding its past information, the second one can be called "Casual" to other one (Granger 1969). Granger Causality formula can be written as:

$$GC_{y \to x} = ln\left(\frac{V_{x|\bar{x}}}{V_{x|\bar{x},\bar{y}}}\right) \tag{1.21}$$

where $0 \leq GC_{Y \to X} < \infty$.

b) Partial Directed Coherence (PDC)

Sameshima et al. (1999), have created new method based on Granger causality which models time series by MAR processes. It is defined as:

$$PDC(f) = \pi_{ij}(f) = \frac{\bar{a}_{ij}(f)}{\sqrt{\bar{a}_j^H(f)\bar{a}_j(f)}} \tag{1.22}$$

where $0 \leq |\pi_{ij}(f)|^2 \leq 1$.

c) Direct Transfer Function (DTF)

Direct Transfer Function is very similar to Partial Directed Coherence and Kaminski et al. (1991) defined it as:

$$DTF(f) = \upsilon_{ij}(f) = \frac{H_{ij}(f)}{\sqrt{h_j^H(f)h_j(f)}} \tag{1.23}$$

1.4.5 Estimation of Statistical EEG Synchronization Between Lobes

a) Mutual Information (MI)

Mutual Information can be used to measure a random variable by observing other variable with quantifying the information amount shared by x & y. If $MI_{xy}=0 \leftrightarrow$ x & y are independent from each other in the formula below:

$$MI_{xy} = \sum_i p(x,y) log \frac{p(x,y)}{p(x)p(y)} \tag{1.24}$$

where $0 \leq MI_{xy} < \infty$. When it is close to 0; x & y are independent and when it is bigger than 0; x & y are dependent to each other (Frenzel et al., 2007).

b) Partial Mutual Information (PMI)

As told in the section above, MI uses the shared information amount between x & y, but it cannot give information about the shared information of third variable (z). For this reason, PMI can be used to measure shared information amount of x & y while eliminating the possibility of z. PMI between x,y and z defined as:

$$PMI(X,Y|Z)= H(X,Z)+H(Z,Y) - H(Z) - H(X,Z,Y) \tag{1.25}$$

Where H is the Shannon's entropy.

c) Transfer Entropy (TE)

Schreiber (2000), proposed the approximated measure of causality calculated by Markov condition below:

$$p(y_{t+1}|y_t^n, x_t^m) = p(y_{t+1}|y_t^n) \tag{1.26}$$

where x_t m= (x_t,x_t+1…,x_t-m+1) and y_t n =(y_t,y_t+1…,y_t-n+1).

Transfer entropy according to x_t & y_t can be defined as:

$$T_{X\to Y} = \sum_{y_{t+1},y_t^{dy},x_t^{dx}} p(y_{t+u}|y_t^{d_y}, x_t^{d_x})\log\left(\frac{p(y_{t+u}|y_t^{d_y},x_t^{d_x})}{p(y_{t+u}|y_t^{d_y}}\right) \tag{1.27}$$

d) Partial Transfer Entropy (PTE)

Similar to Mutual Information and Partial Mutual Information, Transfer Entropy can be partialized. This Partial Transfer Entropy measures the information amount from x to y while decreasing the possibility of z. Runge J et al. (2012) defined PTE with differential entropy(H) and future of x(w) as below:

$$PTE(w,X,Y|Z)=H(w,X,Z)+H(X,Z,Y) - H(X,Z) - H(w,X,Z,Y). \quad (1.28)$$

If both x and y are independent from z, PTE will devolve to TE again.

1.5 EMOTION RECOGNITION

During the past years, the interest for modeling the cognitive processes has been increased in the field of emotion recognition (Lang et al. 1998). The biological needs that form the human behaviors can be divided into two concepts such as preservative and protective concerns (Konorski 1968). In human, the emotional attitude is determined by motivational mechanisms depending on arousal and valance (Cacioppo 1994). Therefore, two emotional dimensions (the affective valence, and the arousal) were taken into account to propose a biphasic emotional model. To propose an emotional model, both single trial EEG measurements and average response of these measurements so called Event-Related-Potentials (ERPs) as well as ERP components such as P300 (the peak recorded 300-400 ms after the stimulus onset) have been analyzed for emotion recognition on either time (Cuthbert et al. 2000, Schupp et al. 2003) or frequency (Basar et al.,1999) domains. In several studies, time and frequency domain analysis are combined to each other (Stam et al. 2002, Inouye et al. 1991).

After Darwin (2002) proposed the first model, first Plutchik (1980) claimed that all emotions can be derived from eight basic emotions which are sadness, fear, anger, disgust, joy, acceptance, surprise and curiosity. Then Ekman (1999) proposed sadness, fear, anger, disgust, happiness and surprise as basic emotions.

In the past few decades, there are many studies on engineering approaches to emotion recognition. They can be categorized into three main approaches which are facial expressions or speech analysis, peripheral signals (ECG, SC, pulse) and brain signals (EEG, fMRI, ECoG) (Wang et al. 2014). EEG-based emotion recognition for evoked emotions is only about 60 percent nowadays, however many researches show the acceptability of EEG for these kind of tasks (Bos 2006).

There are a lot of successful works in the field of emotion by analyzing facial expressions or speech (Kaliouby et al. 2014, Kim et al. 2007). Although most of them are focused on speech signal analysis, facial expression, gestures or text, another approach is physiological signal analysis (Murugappan et al. 2010). Recently, EEG is more trend topic for emotion recognition. Most researchers have used EEG and peripheral signals separately, Chanel and his colleagues paid attention to fuse both systems (Chanel 2009, Chanel et al. 2009, Hosseini et al. 2009). Different researchers have worked on finding the correlation between the emotional changes and EEG signals (Kim et al. 2004). There are a lot of previous works on emotion recognition using EEG signals (Murugappan et al 2010). In 2011, Hosseini et al. (2011) have suggested the brain signals to peripheral signals is because brain signals show direct responses but the peripheral signals are secondary response to emotional stress. Therefore, EEG signals have better time response than peripheral signals.

Some other studies have tried to find how brain activity is associated with different emotional states (Mauss et al. 2009, Lee et al. 2014). The brain's emotional response is not distributed among brain areas. Processing of emotions can be dissimilar in different areas of the brain. For example, the brain-wave activity can be increased by concern and anxiety especially in the frontal and central areas. For instance, when a person is relaxed alpha waves come out well in the brain wave. On contrary, beta waves come out when the person is irritated and gamma come out well when he/she is excited (Ishino et al. 2003). However; there are some categorizing difficulties with EEG signals. One of the reason behind these difficulties is that each person expresses their emotions differently, so differences between emotion categories are not clear. (Murugappan et al. 2010).

Different stimuli types such as auditory, visual or combined can be used in order to evoke emotions and those stimuli types affect different areas of the brain. Most of the experiments that use EEG for emotion recognition, use pictures from the International Affective Picture System (IAPS) or audios from the International Affective Digitalized Sound System (IADS) as stimulus. The usage of IAPS and IADS allows better control of emotional stimuli and simplifies the experimental design (Horlings 2008). Lan et al.

(2016) suggest that, the IADS can be used for the experiment design because the subjects can keep closed their eyes during the exposure to the audio stimuli. By the reason of this, beware of possible movements which could contaminate the EEG signals.

EEG-based technology has been also used in medical applications. With EEG-based emotion recognition, we can recognize emotions from brain signals with a 70-98 percent accuracy, and computers are already successful especially at classifying facial expressions (up to percentage of 80-90) (Bos 2006). EEG results have been improved with the improvements in brain-computer interaction (BCI). Now, correct EEG-based recognition of evoked emotion is only about 60 percent, but many researches show the success of EEG for this kind of task (Bos 2006). To evoke emotions, different stimuli can be used such as auditory or visual. Different areas of the brain can be activated with these stimuli (Liu et al. 2010). In the study of Asakawa et al. (2014), main aim was demonstration of emotional response difference between healthy and psychosomatic patients. Their results indicated that processed information depends on psychosomatic states. For the recognition of the emotions to get better clinical outcomes in PD patients, their results can lead to develop a device which can detect the emotional states automatically (Yuvaraj et al. 2016). However, a feature must show high constancy to be used as clinical. A constant feature should show consistency according to the EEG measurements which are belongs to the same subject (Lan et al. 2016).

It can be seen that two general methods are generally used to model emotions. One method is labeling emotions such as sad, happy, anger, fear, disgust and surprise etc. Another approach is to work on multiple dimensions or scales to categorize emotions (Murugappan et al. 2010). Various machine learning techniques such as KNN, BN, ANN and SVM are used to classify emotional states (Sohaib et al. 2013). Kim et al. (2013) indicated that Wavelet Transform, Fourier Transform and Power Spectral Density are well-known techniques because they are easy implement in real time.

2. EEG-BASED EMOTION RECOGNITION STUDIES

As you can see from the Tables and Appendixes, there are a lot researches about EEG-based Emotion Recognition. They can be compared to each other according to experiment designs (stimulus types, number of channels, number of emotions), feature extraction methods, classifying methods or accuracies.

In the master thesis of Yurci (2014), EEG was recorded from 11 subjects during 6 different music categories (double songs for happy, sad, relax) in his experiment. SVM, Decision Tree, MLP and KNN algorithms have been used on high-level EEG features to detect music category and results were calculated using 10-fold cross validation. Results of different algorithms can be seen in the Table 2.1 below:

Table 2.1: Comparison of different algorithms

Classifier	**Result**
KNN	98.2%
Decision Tree	88%
MLP	75%
SVM	55%

Source: Yurci, E. (2014). Emotion Detection from EEG Signals: Correlating Cerebral Cortex Activity with Music Evoked Emotion. Master Thesis, *Universitat Pompeu Fabra, Barcelona*.

Kim et al. (2004) used the music and story as stimuli on fifty participants for 3 and 4 categories of different emotions. They have reached to accuracy of 78.4 percent for 3 emotions and 61 percent for 4 emotions. When they used music as stimuli, their accuracy results were increased to 92 percent and 88.64 percent for even high number of categories.

Ishino et al. (2003), calculated correlation between EEG brain waves and feelings. Then they used Gabor wavelet transform and FFT to extract features and feedforward neural network to classify feelings. The neural network was learned by the back propagation algorithm. They reached to maximum accuracy of 54.5 percent for joy to 67.7 percent for anger.

Chanel et al. (2006) were trying to distinguish calm, neutral and excitement signals with simple feature extraction methods and Naive Bayes classifier. One year later, their work was improved by Ansari et al. (2007) with using Synchronization Likelihood method. They have also used Hjorth Parameters and Fractal Dimensions for feature extraction and LDA for classification. The results had the accuracy of 60 percent. In 2009, Chanel (2009) asked the participants to remember their past as stimuli, and had the accuracy of 88 percent with SVM by combining EEG and peripheral signals for 3 categories in his new study. The best result was 79 percent when they use only EEG, and 53 percent for only peripherals. Other researchers Sadock et al. (1998) also used peripheral signals in their research, had fifteen healthy males between the age of 20 and 24 to record EEG at 5 positions by the international 10-20 system. Khalili et al. (2008), they used Calm (C), Positively Excited (PE), and Negatively Excited (NE) stimuli from IAPS. They have used statistical features such as Mean, Standard deviation, Skewness, Kurtosis, Mean of the absolute values of the first difference of raw & normalized signals. They have also used peripheral signals such as galvanic skin resistance, respiration, blood pressure and temperature for their experiment. KNN and LDA were used for classifying and GA to solve high dimensional feature problem. Time-domain and frequency-domain features of brain signals were evaluated separately. Combining brain and peripheral signals gave the accuracy results of 51 percent and 67 percent for three and two categories, respectively. In 2009, they added correlation to their features. Their study also showed that using KNN concluded in better results. Hosseini et al. (2009) used images as stimulus to record the EEG and peripheral signals for Calm-neutral and Negatively-exited, and reached the accuracy of 78.3 percent with SVM classifier.

Schaaff et al. (2009) used pictures from IAPS to stimulate neutral, pleasant and unpleasant emotions for 5 male subjects. They reached to the accuracy of 66.7 percent by using FFT for feature extraction and SVM for classification.

Macas et al. (2009), obtained EEG signal by 19 channels in international 10-20 system from 23 subjects. They used four categories of the pictures from IAPS with 25 stimuli.

They used statistical analysis (mean, standard deviation, skewness, kurtosis) of EEG and ECG. In addition, Shannon's entropy of wavelet transforms was used to extract features and 75 percent of accuracy has been reached by Bayes Tree algorithms.

Bos (2006) have used 5 test subjects (4 females, 1 male) with only five electrodes. For her experiment, 36 emotion stimuli were selected from IADS and IAPS databases. She applied Fourier transform and bandpass filtering to extract features. She has reached to 82.1 percent for Modality, 97.4 percent for Arousal and 94.9 percent for valence. In addition, in her study, binary classification rates showed minimum accuracy of 90 percent for each of the tested features and when there was no dimensional overlap, accuracy was reduced to 80 percent. Sohaib et al. (2013) obtained EEG signal from 15 men and 5 women with international 10-20 system and also used IAPS database. Machine learning techniques such as KNN, BN, ANN and SVM were used for classifying. The result was 56.10 percent in the best case but the accuracy rose to 77.78 percent when they divided the subset into four parts with five subjects each. SVM and KNN gave the best results as classifiers. When only single data was used, KNN classifier gave 83.33 percent accuracy.

In the study of Jenke et al. (2014), there were 7 women and 9 men and for each emotional state, EEG was recorded with a 64-channel device according to the international 10-20 electrode system. All happy, angry, sad, quiet and curious emotions are activated by IAPS dataset. 22881 features were extracted from 64 electrodes and leave-one-out cross validation was used to decrease the number. QDA and Naïve Bayes were used for classification. Their results showed that emotion happy is generally better recognized than emotion sad.

EEG was recorded from 129 electrodes in 10 (7 Female / 3 Male) subjects IAPS stimuli in the experiment of Keil et al. (2001). Frequency measurements and ERPs were obtained for pleasant, neutral, and unpleasant emotions. EEG was recorded with 128-channel system and SAM was used also. Accuracy result after ANOVA classifier was $p<0.01$ as expected.

MI and magnitude squared coherence are applied to investigate the interconnectivity between 8 scalp regions in the study of Khosrowabadi et al. (2010). Experiment was performed to collect 8 channels of EEG data from subjects, pictures from IAPS were used together with musical stimulus for four basic emotions of calm, happy, sad and fear by using the International 10-20 system. The emotions can be different in every subjects, because of that, SAM was used to rate emotions in arousal and valence scales. Magnitude Squared Coherence and Mutual Information for EEG signals were used to extract EEG features for classification. Then, KNN and SVM classification techniques were performed onto EEG features and the by using 5-fold cross-validation, performance of the EEG-based emotion recognition system was evaluated. The results indicated different kind of functional brain connectivity in different emotional states.

Balconi et al. (2009) used 32 channel EEG device in international 10-20 system for 25 (15 Male /10 Female) participants during exposure of 25 pictures selected from IAPS database for pleasant, unpleasant and neutral emotions. They have also recorded EOG to remove eye movements. Bandpass filter was applied to EEG signals to calculate power values for each frequency bands. By using of correlation analysis, EEG coherence was computed between each electrode for anterior, central and posterior regions and two hemispheres for selected emotions. By their power spectra, spectral cross-correlation was normalized. Then ANOVA was applied to obtain the results listed below:

a. Both valence and arousal main effects were significant ($P < .01$).
b. For delta band, coherence analysis had significant effect with an increased delta coherence within the posterior than anterior and central localization
c. Theta showed presence in frontal right cortical region
d. For gamma band, frontal right activity was increased
e. For Alpha band, there was no important effect of coherence analysis
f. Delta and theta band have a main role in monitoring the attentional significance of emotions.

Murugappan et al. (2010), have used 20 students recorded their brain waves with 64 electrodes by international 10-10 system. Surface Laplacian (SL) filter was applied to remove noises and artifacts. Then, they have used the FCM and FKM for classifying the human emotions and two simple classifiers such as KNN and LDA for pattern classification. Another method was proposed by Murugappan et al. (2010) was based on DWT and they reached to maximum accuracy of 83.26 percent for five emotions. They have also calculated intra-hemispheric and inter-hemispheric EEG coherences and correlations between EEG electrodes and obtained 93 features in total. 5-fold cross-validation was used for classification and the accuracy of 75 percent was reached. Their main aim was to show EEG-based functional connectivity of different emotional states. We can obtain the following results from their work:

1. Positive emotional state has higher correlations in the temporal site of right hemisphere and it is also more synchronized than negative emotion at each frequency band.
2. Coherence was greater during negative emotion than during positive emotion especially in the occipital and right parietal areas.
3. Correlation and coherence analyses showed similar patterns.
4. Especially at the occipital and temporal sites, the negative emotional states had higher correlation and coherence than positive emotional states

In the study of Lee et al. (2014), EEG was recorded with 64-channel according to the international 10-20 system from 40 subjects. They used emotional movie clips for neutral, positive, and negative. In order to filter eye movement artifact, 2nd order bandpass Butterworth filter was used. EEG signal was converted to frequency domain via FFT to estimate coherence, and signal phase was obtained for computing phase synchronization. They have used QDA to fast evaluations and 2-fold cross validation for pattern classification and result of the classifications is calculated by paired t-test. They reached to a conclusion of; higher correlation and coherence corresponds to stronger relationship between brain sites. Their results showed that EEG-based functional connectivity estimation is helpful to indicate brain activity and emotional states relation.

In the study of Li et al. (2009), EEG was recorded over four dry electrodes according to the International 10–20 system from 5 Chinese subjects. They used ‘Youtube’ videos as stimuli and extracted 6 features in time domain and classify emotions by RVM and SVM methods. With the usage of 10-fold cross validation method, accuracy was found as 97.82 percent for 24 features with RVM and SVM. Lin et al. (2010) used 26 subject and musical stimuli for joy, pleasure, sadness and anger and also applied support vector machines to classify these 4 emotions with the accuracy of 82.29 percent.

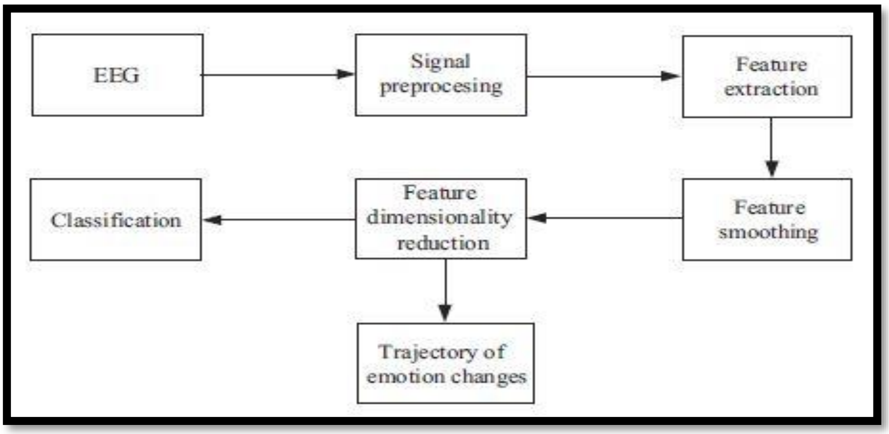
Trochidis et al. (2012) used sixteen participants (8 males and 8 females) and recorded EEG from 64 scalp locations according to the international 10-20 system with audial stimuli for happiness, anger, sadness and serenity emotions. For each condition, power spectra were computed via FFT after removing spectral artifacts by Hamming function and then mean power spectrum was calculated. They found that theta power has more important role on emotion recognition with music stimuli.

Takahashi (2004) used film clips to stimulate participants with 3 channel EEG device for five different emotions (joy, anger, fear, sadness, and relaxation) based on bio-potential signals (EEG, pulse, and skin conductance) to detect patterns correctly by applying SVM, FDA and naïve BN. He has reached the accuracy of 41.7 percent with 5 emotions. On the other hand, when he used 3 emotions (happy, sad and relaxed), the result was 86.25 percent.

Wang et al. (2014) used six movie clips (positive and negative emotions) for six healthy volunteers (three males and three females), and record EEG by 62-channel electrode cap with international 10–20 system. In order to remove eye movements, EOG was also recorded. They investigated emotion-specific features such as power spectrum, wavelet and nonlinear dynamical analysis. They also used feature dimensionality reduction with PCA, LDA and CFS and reached to accuracy of 91.77 percent when dimension number was reduced to thirty with SVM and 10-fold cross-validation.

The EEG data were analyzed as the flow in Figure 2.1.

Figure 2-1: The flowchart of emotional state classification



Source: Wang, X. W., Nie, D., & Lu, B. L. (2014). Emotional state classification From EEG data using machine learning approach. Neurocomputing,129, 94-106.

In the study of Liu et al. (2010), 26 subjects were used to obtain EEG with 32 channels by using IADS database. Then, STFT was used to calculate the power difference between 12 electrodes pairs to extract feature and classification was done by multi-class SVM from those features. Before SVM, they have also used some optimization techniques such as normalizations, filters and dimensionality reduction methods to increase accuracy and they have reached the accuracy of 90.72 percent for joy, pleasure, sadness and anger.

In the experiment of Lan et al. (2016), EEG was recorded for twice per day for 8 consecutive days from five subjects during audio-visual stimuli from IADS for pleasant, happy, frightened and angry. Statistical properties were extracted which are standard deviation and mean of absolute values of the first diversities, mean of absolute values of the first diversities of normalized, mean of absolute values of the second diversities, mean of absolute values of the second diversities of the normalized EEG. In their paper, constancy of different EEG features for real-time emotion recognition was analyzed. They have reached to maximum of 71.75 percent for any two emotions and 73.10 percent for positive emotions.

Kvaale (2012) have used 32 participants (50 percent female) in his master thesis with the goal of detecting emotions with computerized systems. He got helped from BCI methods and used FFT to work on frequency domain. ANN was used by training via HyperNEAT (neuro-evolutionary method as trainer) and reached to accuracy of 80.6 percent.

Aydin et al. (2015) used 10 subjects (5 females and 5 males) and recorded EEG with international 10-20 system in 19 channels. Mean coherence and mutual information were used as features to get inter-hemispheric dependencies between 2 different channels. Accuracy of 75.50 percent for Coherence and 77.94 percent for Mutual information has been reached by using SVM and 2-fold cross-validation.

In the study of Bajaj et al. (2014), EEG signals have been recorded with 16 channel from 8 subjects (8 Male and 8 female) with the stimulus of audio-visual. When multiwavelet decomposition is used, it is possible to get better accuracy from EEG signals in contrast to not using it. According to classify the different emotions, firstly

EEG signal decomposed into sub-signals of it, then Euclidian distance's mean and standard deviation are taken into account as input features to the multi class least squares support vector machines (MC-LS-SVM) In addition, as you can see from the Table 2.2, Bajaj et al. (2014) compared different techniques from other proposed experiments for EEG-based emotion recognition. Then, they proposed their new method with MC-LS-SVM and reached to higher accuracy. Extracting features from sub-signals of EEG with multiwavelet decomposition and MC-LS-SVM provides 91.04 percent accuracy.

Table 2.2: Comparison of different techniques

Methods	**Results**
Mahalanobis Distance (MD) & SVM	79.5% & 81.3%
SVM with Time-frequency based features	63.8%
Surface Laplacian & Wavelet Transform & Linear Classifier, KNN Surface Laplacian & Wavelet Transform & Linear Classifier, LDA	83.04% 79.17%
SVM with STFT	82.29%
HOC-based features of 6 emotions	83.33%
Time & Frequency based for 4 emotions	66.5%
Spectogram, Zhao-Atlas Marks and Hilbert-Huang	86.52%

Source: Bajaj, V., & Pachori, R. B. (2014, May). Human emotion classification from EEG signals using multiwavelet transform. In *Medical Biometrics, 2014 International Conference on* (pp. 125-130). IEEE.

The aim of Chandra et al. (2016) was to analyze the effects of gender difference on different emotional states. Movie clips were used as stimulus to 18 (9 Female/9 Male) subjects to stimuli positive, negative and neutral emotions. They analyzed brain connectivity and functional index in terms of coherence on alpha, beta and theta frequency bands in 14 electrode channels. The P value of ANOVA measurement was smaller than 0.001 for each positive, negative and neutral emotion levels. Below statements (Table 2.3) can be obtained from their study results:

Table 2.3: Experiment results of Chandra's study

Statement	Men	Women
Coherence FCN	Greater during negative	Greater during positive emotion
Local & Global Efficiencies	Higher during negative emotion	Higher during positive emotion
During negative Emotion	Right-hemispheric Activation	Left-Hemispheric Activation
Connectivity	Strong on Frontal Region	All regions of brain
Parietal Region Activation	Both men and women show activation during Neutral emotions	
Prefrontal-temporal	Both men and women show activation during Fearful vs. Enjoyable	

Source: Chandra, S., Sharma, G., Rizvi, A., Gupta, N., Mittal, A. P., & Jha, D. (2016). Gender Differences with Different Emotions for Brain Functional Connectivity analysis. *International Journal of Scientific Research in Information Systems and Engineering (IJSRISE)*, *2*(1), 1-8.

As a conclusion, when advertisement is perceived as positive by participants, left hemisphere become more active. In the other hand when it is perceived as negative, right hemisphere become more active. When it comes to the men with negative emotions, the efficiencies are higher.

Petrantonakis et al. (2011) recorded 16 subjects in 3 channels to introduce Asymmetry Index (AsI) in frontal brain by analyzing EEG signals between opposite brain hemispheres. EEG signals were taken from the left and right frontal, central, anterior temporal, and parietal regions of F3, F4, C3, C4, T3, T4, P3, P4 positions according to the 10–20 system. Band-pass butter-worth filtering were used after acq part Feature-vector extraction methods were applied in order to calculate efficiency of AsI, and SVM was used as classifier. As a result, the efficiency of AsI as an index for the emotion elicitation evaluation, for the user independent case 62.58 percent and 94.40 percent for the user dependent one. Main result for their study is that processing negative emotions are harder than positive emotions. Response time and accuracy advantages to positive over negative are reported.

Late studies show that right hemisphere has a unique contribution to emotion processing. 14 channel EEGs from 20 (10 Female /10 Male) PD patients and 10 healthy age-matched controls were recorded by revealing emotions such as happiness, sadness, fear, anger, surprise and disgust in the experiment of Yuvaraj et al. (2016). IAPS and IADS databases were used as stimulus for 6 s. Thresholding method were used to pre-process the time series waveform of EEG data for removing artifacts. Approximate Entropy, Fractal Dimension, Correlation Dimension, Hurst Exponent, Detrended Fluctuation Analysis, High Order Spectrum, Sample Entropy, and Largest Lyapunov Exponent are the non-linear methods in order to extract the features from the pre-processed EEG signals. By the use of these methods and bandpass filter, 11 non-linear features were extracted. Accuracy of 71.42 percent and 83.39 percent were reached with Fuzzy kNN and SVM classifiers respectively.

In the study of Flores-Gutiérrez et al. (2009), gender differences in EEG coherent activity were investigated during satisfying and non-satisfying musical emotions. Detection and analyzing the neural patterns or networks of coherent activity between brain’s cortical regions during pleasant and unpleasant musical emotions in men and women is the aim of this study. 19 Channels of EEG data was recorded in international 10-20 system from 14 (7 Male /7 Female) subjects during musical stimulus by J.S. Bach. Cross-correlation between electrode pairs were calculated before applying FFT. Then, Fisher’s Z scores were used for evaluating these correlation values after decreasing the number of variables with PCA. Results can be seen in the Table 2.4 below:

Table 2.4: Experiment results of Flores-Gutierrez’s study

Statement	**Comparison 1**	**Comparison 2**
Coherent Oscillations during Pleasant emotions	Left Hemisphere	Larger in women
Coherent activity during Unpleasant Emotions	Between midline and posterior regions in right	Anterior regions in women

	hemisphere in men	
Coherent activity during pleasant musical emotion	Frontal region on left	
Pleasant emotions	Left hemisphere in women	Left hemisphere in men
Unpleasant emotions	Bilateral network in women	Right hemisphere in men
Intra-hemispheric Correlation	Lower in women	Higher in men
Inter-hemispheric coherent	Higher in women	Lower in men
Unpleasant Visual Stimuli	Higher Right sided activation within frontal regions in women	Lower Right sided activation within frontal regions in men
Coherent Alpha Activity during Pleasant Musical Emotion	Posterior and frontal of left hemisphere in women	Posterior and frontal of left hemisphere in men
Coherent Network for musical emotion	Larger in women	Lower in men
Facial expression recognition	Faster in women	Slower in men
Identifying Non-verbal info	Better in women	Worse in men

Source: Flores-Gutiérrez, E. O., Díaz, J. L., Barrios, F. A., Guevara, M. Á., del Río-Portilla, Y., Corsi-Cabrera, M., & del Flores-Gutiérrez, E. O. (2009). Differential alpha coherence hemispheric patterns in men and women during pleasant and unpleasant musical emotions. *International Journal of Psychophysiology*, *71*(1), 43-49

Main result of their study is that men and women should not be analyzed together especially in the emotion recognition studies that used musical stimuli.

Ramirez et al. 2012 have obtained EEG from 6 subjects (3 female and 3 male) with 14 electrode channels in international 10-20 system. 12 audial stimuli were chosen from IADS database for three positive/aroused, three positive/calm, three negative/calm, and three negative/aroused. LDA and SVM were applied to classify emotional states and accuracy of 80.11 percent has been reached.

Lee et al. (2006) wanted to work on frequency domain in order to classify brain states with EEG. They have used features such as mean spectral power, mean sample value, mean phase angle, peak frequency and peak frequency magnitude, zero crossing rate, number of samples above zero and the mean spectral power difference. Accuracy of 84 percent has been reached by BN as classifier and 10-fold cross-validation.

3. RESULTS

Table 3.1: Emotion Recognition with Brain Connectivity Measurements

Authors	Features	Methods	Accuracy
Balconi 2009	Coherence Correlation CC	ANOVA	P < 0.1
Khosrowab 2010	MI Coherence	CC, CV, SVM	85%
Chandra 2016	Connectivity Index Coherence	ANOVA	P<0.001
Petrantonakis 2011	HOCs, CC	BW, SVM	62.58%
Flores 2009	CC	FFT,PCA	<0.0001
Macas 2009	Stats, Coherence, Correlation	WT,CV,BN	75.00%
Lee Y 2014	Coherence, PS	BW,FFT, QDA,LDA,CV	NA
Khalili 2009	Stats, Correlation	KNN, peripheral,LDA,GA	76.66%
Ishino 2013	Correlation, bands	FFT,WT,NN	67.7%
Bolte 2003	Coherence,RECALL	ANOVA	p<0.001
Jenke 2014	Coherence, PS	CV, QDA, NaiveBN	61.00%
Schaaf 2009	Mean+std, CC	SVM	47.11%

a. Many researchers have focused on Brain Connectivity Measurements to estimate emotions from EEG measurements and these studies are listed in Table 3.1 and Appendix A.1. They all agreed to that; brain activities can differ with different emotions (Balconi 2009; Khosrowab 2010; Chandra 2016; Petrantonakis 2011; Flores 2009; Macas 2009; Lee Y 2014; Asakawa 2014; Khalili 2009; Ishino 2013; Bolte 2003; Jenke 2014; Schaaf 2009)

b. When music is used as stimuli to the participant, it is shown that accuracy rates have increased. (Kim et al. 2004; Trochidis et al 2012; Lin et al. 2010; Yurci 2014)

c. Using EEG and peripheral signals together increases the accuracy (Chanel 2006; Chanel 2009; Sadock et al 1998; Khalili et al 2008; Hosseini et al 2009; Hosseini et al 2011)

d. Using the suitable stimuli is essential to improve emotional response. As a result of reviews on emotion recognition studies based on EEG (Table 4.1) the most efficient stimuli type is audio-visual type according to the reviewed studies. (Bajaj et al, 2014; Chandra et al 2016; Khosrowabadi et al 2010; Asakawa 2014; Bos 2006; Kim 2004; Lee 2014; Li 2009; Murugappan 2009; Takahashi 2004; Wang 2014)

e. Dimensionality reduction also increases the accuracy results (Liu et al 2010; Wang et al 2014; Bos 2006; Khalili et al 2008).

f. Studying on frequency domain with FFT can be a better solution for classification problems (Ishino et al 2003; Schaaf et al, 2009; Lee et al 2014; Trochidis et al 2012; Kwaale 2012; Bos 2006; Kim et al 2013).

g. Considering the results in Table 3.2; the most successful emotion classification was done using Support Vector Machine (SVM) due to its effectiveness and better accuracies (Bajaj 2014; Brown 2011; Chanel 2009; Chanel Ee al 2009; Frantzidis 2010; Hosseini 2009; Hosseini 2011; Khosrowab 2010; Kim et al 2013; Lan 2016; et al 2009; Lin et al 2009; Lin et al 2010; Lin et al 2010; Liu 2010; Liu 2013; Murugappan 2011; Petrantonakis 2010; Petrantonakis 2011; Ramirez 2012; Sadock 1998; Schaaf 2008; Schaaf 2009; Sohaib 2013; Sohaib 2013; Takahashi 2004; Wang 2014; Wang 2011; Yurci 2014; Yuvaraj 2016)

h. Artifact removal is very important in order to obtain good features and better accuracies. (Murugappan et al 2010; Lee et al 2014; Trochidis et al 2012; Yung 2000; Wang et al 2014)

Table 3.2: Emotion Recognition Studies with SVM Classifier

Authors	# of Emotions	# of Channels	Other Methods	Accuracy
Yurci 2014	?	?	DT kNN	98.2% 88.9%
Li M 2009	3	4	FCM	97.82%
Li M et al 2009	2	62	Logarithmic variances	93.50%
Murugappan 2011	5	62	Statistical Features	93.04%
Wang 2014	2	62	PowerSpectrum,WT,CV	91.77%
Bajaj 2014	?	16	ButterWorth, WT, CV	91.04%
Lin et al 2009	4	32	Power differences	90.72%
Liu 2010	4	32	FFT, BandPass, WT,	90%
Hosseini, 2011	4	5	WT, NN, CV	88.5%
Chanel 2009	3	?	Naïve, BN	88%
Takahashi 2004	5	3	Naïve BN, FDA	86.25%
Liu Y 2013	8 2	4	Statistical & HOC	83.73% 53.75%
Yuvaraj 2016	6	14	BW, thresholding	83.39%
Petrantonakis 2010	6	4	ERS+EDS+HOCs + SVM ERS+EDS+HOCs + QDA	83.30% 62.30%
Lin et al 2010	4	32	Power spectra	82.29%
Lin Y.P.et al,2010	4	32	STFT	82%
Frantzidis 2010	4	?	ERP and Oscillations	81.30%
Ramirez 2012	4	?		80.11%

Hosseini, 2009	3	?	Peripherals	78.3%
Lan 2016	4	14	Stats, HOCs, Bands, CV	73.30%
Wang X.W. 2011	4	62	Stats, Power	66.51%
Brown 2011	3	8	Power + Bands	64%
Chanel G. Et al 2009	?	64	STFT	63.00%
Petrantonakis 2011	?	?	BW	62.58%
Schaaf 2008		16	STFT	62.07%
Sohaib 2013	3	6	Statistical	56.30%
Schaaf 2009	3	4	Mean+Std, CC	47.11%
Kim 2013	?	?	WT, FT, PSD, DA, MD, KNN	?
Sadock 1998	?	5	DWT, GA	?
Sohaib 2013	?	?	ICA	?
Khosrowab 2010	4	8	MSCE, CC, CV, SAM	?

4. DISCUSSION AND CONCLUSION

The goal of this study was to compare previous studies in literature about EEG based emotion recognition. Main aim was to find the optimal experiment setup and methods by reviewing recent and successful studies (Table 4.2) as listed in Appendix A.1. Computers can reach the percentage of 80-90 of average accuracy even though humans can classify the emotions with 70-98 percent accuracy. However, in order to reach this high success rate, we have to choose best methods for all the EEG acquisition, filtering, preprocessing, feature extraction, processing, classifying steps.

As you can understand from above, every step of emotion recognition based on EEG signals affects the result beginning from obtaining EEG signal.

Brain signals and connectivities have more direct effects with emotion change, however peripheral signals are secondary response to emotions. Also the brain signals have better response time than peripheral signals. Therefore, as you can see from above, using peripheral signals as secondary information to increase classify success is better option (Hosseini et al. 2009).

Generally, international 10-20 or 10-10 electrode system is used to obtain EEG signal from brain. Signals belongs to specific emotions can differ with respect to the different brain areas (Asakawa et al. 2014).

EEG signals can be processed in both time domain and frequency domain (with FFT).

Using the correct stimuli is also important to increase the emotion effects on EEG signals. IAPS and IADS are the most important databases for high quality stimuli. Most successful accuracies generally were obtained by using audio-visual stimuli. The studies including audio-visual stimuli to evoke discrete emotions are listed in Table 4.1.

Table 4.1: Emotion Recognition Studies with Audio-visual Stimulus

Study	**Number of Emotions**	**Methods**	**Accuracy**
Bajaj et al, 2014	Different Emotions	Butterworth, **multi-wavelet** 10-fold Cross-validation, Confusion matrix	91.04%
Chandra et al, 2016	3		smaller than 0.001 for each positive, negative and neutral
Khosrowabadi et al, 2010	4	MSCE, MI, CC, 5-fold CV SAM	
Asakawa, 2014	3		
Bos DO, 2006	U/K*	Bandpass Fourier PCA	82.1% modality 97.4% arousal 94.9% valence
Kim, 2004	U/K	U/N	78.4% (3) 61% (4)
LeeY., 2014	3	Butterworth FFT PS	U/N
Li M., 2009	3	FCM	97.82%
Murugappan,2009	6	DWT	Higher in alpha
Takahashi, 2004	5	U/N	42% 86.25% (3)
Wang, 2014	2	PCA LDA CFS 10-fold CV	91.77%

*U/K: Un-Known

Pre-processing is also important for analyzing the EEG data to obtain better feature extraction results. However, the complete removal of artifacts can also remove some of the useful information of EEG signals (Jung 2000). Extracted features must be chosen carefully for easy emotional state classification.

In the end, the general purpose of all the studies in this area is to evaluate different techniques for better emotional state classification of EEG data. From these previous studies, we can see that, combining all the methods that give the high success rate for emotion recognition, can give the highest classification accuracy.

Table 4.2: Emotion Recognition Studies that Gave 10 Highest Accuracies

Authors	Experiment	Features	Feat.Extr. Methods	Classifiers	Emotions	Stimuli	Results
Li M., 2009	5(3M/2F) 4channel	bands	FCM	RVM SVM	Happy sad relaxed	Audio-visual	97.82 %
Wang, 2014	6(3M,3F) 62channel	Power spectrum Wavelet	PCA LDA CFS 10-fold CV	SVM	Positive negative	Movie clips	91.77 %
Bajaj et al, 2014	8(4M,4F) 16Channel	Euclidian distance's mean and standard deviation	Butterworth, multi-wavelet 10-fold Cross-validation, Confusion matrix	Morlet Wavelet Kernel function of MC-LS-SVM	Different emotions	Audio-visual	91.04 %
Hosseini, 2011	15 5channels	Stats FD CD ApEn HOCs	WT NN 5-fold CV	SVM ENN	Calm-neutral Negatively-excited	IAPS	88.5%
Chanel, 2009	64 channels	Bands MI peripherals	FFT Bandpass	SVM Naïve BN	Excitement Neutral calm	recall	88%
Khosrowabadi et al, 2010	26subjects 8channel	Mutual information and magnitude squared coherence	MSCE,MI,CC, 5-fold CV SAM	KNN SVM	Calm,sad Happy,fear	IAPS Audio-visual,1min	85%
Lee J. et al, 2006	8(5M/3F) 2channels	Spectral-Power Statistical	FFT 10-fold CV	BN	Task based	audio	84%
Petrantonakis, 2010	3channel 16subjects	ERD ERS	HOC	QDA SVM	6	Ekmans' picture set	83.33% SVM 62.3Q% DA
Murugappan, 2010	20(17M,3F) 64channel	FCM FKM	SL DWT	KNN LDA	6	IADS	83.26%
Lin, 2010	32channel	Freq bands Power spectra	STFT	SVM	Joy,anger Sad pleasure	music	82.29%

Methods that gave the high success can be listed as:

a. International 10-20 electrode rule
b. Audio – visual stimuli (remembering past memories)
c. Preprocessing filters
d. Using less features
e. Using more EEG channels
f. Frequency domain with Fourier Transform
g. Discrete Wavelet Transform
h. Genetic Algorithm for solving high dimensionality problem
i. Support Vector Machine (SVM), Relevance Vector Machine (RVM)

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APPENDIX

Appendix A.1: Review Table for EEG-based Emotion Recognition Studies

Authors/year	Experiment	Features	Feat.Extr. Methods	Classifiers	Emotions	Stimuli	Results
Ansari, 2007	1male 64channels	Hjorth parameter Fractal Dimensions	Sync likelihood(SL)	LDA	Positive Negative calm	RECALL	60%
Aydin S. et al (2015)	10(5/5) 19	Coherence MI		SVM			
Bajaj et al, 2014	8(4M,4F) 16Channel	Euclidian distance's mean and standard deviation	Butterworth, multi-wavelet 10-fold Cross-validation, Confusion matrix	Morlet Wavelet Kernel function of MC-LS-SVM	Different emotions	Audio-visual	91.04 %
Balconi et al, 2009	25(15/10) 32channel	Coherence Correlation CC	ANOVA	ANOVA	Pleasant Unpleasant Neutral	IAPS 6s	P<.01
Bos DO, 2006	5(4M,1F)	f.bands	Bandpass fourier PCA	FDA	36	Visual Audio Audio-visual IADS IAPS	82.1% modality 97.4% arousal 94.9% valence
Chandra et al, 2016	18(9M,9F) 14Channel	connectivity index Coherence bands	bandpass	ANOVA	neutral, positive, or negative	film clips	smaller than 0.001 for each positive, negative and neutral
Chanel, 2009	64channels	Bands MI peripherals	FFT Bandpass	SVM Naïve BN	Excitement Neutral calm	recall	88%
Flores et al, 2009	14(7M,7F)	Correlations Alpha	FFT CC PCA	Fisher-z scores	pleasant and unpleasant	music	The women have larger coherent network.
Hosseini, 2011	15 5channels	Stats FD CD ApEn HOCs	WT NN 5-fold CV	SVM ENN	Calm-neutral Negatively-excited	IAPS	88.5%
Ishino, 2013	3electrodes	Correlation Wavelet T Amplitude Power spectrums	FFT Maximum entropy Gabor-wavelet	Forward-NN	Joy anger sorrow relaxation	Music Video Puzzle	54.5% joy 67.7% anger
Jenke et al, 2014	16(9M,7F) 64channel	leave-one-out	Leave-on-out cross	QDA	Happy, Curious,	IAPS	emotion happy is generally

		cross validation	validation, SAM		angry, sad, quiet		better recognized than emotion sad
Keil et al, 2001	10(3M,7F) 128channel	Freq and ERPs	ANOVA,SAM	ANOVA	Pleasant Neutral Unpleasant	IAPS,1s	P < 0:01 ?????
Khalili, 2008	5 64 channels	Statistical peripherals	LeaveOneOut CV GA bandpass	KNN LDA	Positive Negative Calm	IAPS	51% 67%
Khalili, 2009	5 54	Statistical Correlation peripherals	LeaveOneOut CV GA bandpass	QDA	Positive Negative Calm	IAPS	66.6% 76.6% (Correlation dimenstion)
Khosrowabadi et al, 2010	26subjects 8channel	MI and magnitude squared coherence	MSCE,MI,CC ,5-fold CV SAM	KNN SVM	Calm,sad Happy,fear	IAPS Audio-visual,1 min	85%
Kim, 2004	125+50	peripherals	FDA	SVM	Sad, anger, stress, surprise	Audio-visual	78.4% (3) 61% (4)
Kvaale, 2012	32(16/16)	Beta gamma	FFT	ANN	Arousal valence		80.6%
Lan et al, 2016	5(4M,1F) 14channel	Statistical Features HOCs Power bands	5-fold CV	SVM	Pleasant Happy Angry frightened	DEAP IADS	71.75% 73.10%
Lee&Tan, 2006	8(5M/3F) 2channels	Spectral-Power Statistical	FFT 10-fold CV	BN	Task based	audio	84%
LeeY., 2014	40(21M,19F) 64channel	coherence	Butterworth FFT PS	QDA LDA 2-fold CV	Neutral Positive negative	Film clips	Func.connectivity is good for EEG-bsed E.R.
Li M., 2009	5(3M/2F) 4channel	bands	FCM	RVM SVM	Happy sad relaxed	Audio-visual	97.82%
Lin, 2010	32channel	Freq bands Power spectra	STFT	SVM	Joy,anger Sad pleasure	music	82.29%
Liu, 2010	26 32channel	FFT	Band-pass wavelet	SVM RVM FCM	Joy,sad Anger pleasure	IADS	90%
Macas, 2009	23 19channel	Statistical Coherence Correlation HRV	Wavelet 5-fold CV	bayes	Pleasant Ugly Boring arousing	IAPS	75%
Murugappan, 2010	20(17M,3F) 64channel	FCM FKM	SL DWT	KNN LDA	6	IADS	83.26%
Murugappan,2009	6(3M,3F) 63channel	bands	DWT	FCM	6	Movie clip	Higher in alpha
Panat, 2013		Statistical	wavelet	LDA KNN FDA			
Petrantonakis et al, 2011	16(9M,7F)	AsI HOCs	butterworth	QDA MD		IAPS,11 s	62.58%

		CC		SVM			
Petrantonakis, 2010	3channel 16subjects	ERD ERS	HOC	QDA SVM	6	Ekmans' picture set	83.33% SVM 62.3% QDA
Ramirez, 2012	6(3/3) 4channels	bands	Bandpass FFT EOG	LDA SVM	Positive Calm Negative aroused	IADS	80.11%
Sadock, 1998	15M 5channel	DWT	GA	SVM RBF			
Schaaf, 2009	4channel	Cross-correlation features	5-fold CV	KNN LDA	Pleasant Unpleasant neutral	IAPS	66.7%
Sohaib, 2013	20(15M,5F) 6channel	Stats peripherals	ICA FFT WT Thresholding	KNN BN KNN SVM ANN	Positive Negative Neutral calm	IAPS 5s	56.1% 77.8% 83.3%
Takahashi, 2004	12 3channel	bands peripherals	Low-pass	Naïve-BN FDA SVM	Joy,anger Sad,fear relax	Movie clips	42% 86.25% (3)
Trochidis, 2012	16(8/8) 64channel	Power Spectra	Hamming FFT	ANOVA	Happiness Anger Sadness serenity	musical	P<0.05
Wang, 2014	6(3M,3F) 62channel	Power spectrum Wavelet	PCA LDA CFS 10-fold CV	SVM	Positive negative	Movie clips	91.77%
Yurci, 2014	11(9M/2F) 14channels	Bands Arousal-valence	bandpass	DT KNN MLP SVM	Happy Sad relax	music	98.2% DT 88.9% KNN 75.8% MLP 53.5% SVM
Yuvaraj et al, 2016	10M/F PD 10Healthy 14channel	AE, CD, DFA, FD, HOS, HE,SE LLE**	Thresholding Butterworth	Fuzzy kNN SVM ANOVA	Happy Sad,fear Anger Surprise disgust	IAPS IADS 6s	71.42% 83.39%