ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE
ENGINEERING AND TECHNOLOGY

FUZZY COGNITIVE MAPS FOR EMOTION MODELING

M.Sc. THESIS

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Department of Control Engineering

Control and Automation Engineering Programme

JULY 2013

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

BULANIK BİLİŞSEL HARİTALAR YARDIMIYLA İNSAN DUYGULARININ MODELLENMESİ

YÜKSEK LİSANS TEZİ

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Hasan Murat AKINCI, a M.Sc. student of ITU **Graduate School of Science Engineering and Technology** student ID 504091128, successfully defended the thesis entitled **"FUZZY COGNITIVE MAPS FOR EMOTION MODELING"**, which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : **28 August 2013**
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To my mother and father,

FOREWORD

First, I would like to thank my supervisor Asst. Prof. Dr. Engin Yeşil, whose support and advice were invaluable in the production of this thesis. I'd like to thank my teacher Prof. Dr. Ibrahim Eksin and Prof. Dr. Müjde Güzelkaya for their support during my master. Lastly, I would like to thank all my friends and of course my family for their support.

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Hasan Murat AKINCI
Control Engineer

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ABBREVIATIONS

FCM	: Fuzzy Cognitive Map
BBBC	: Big Bang Big Crunch
EEG	: Electroencephalography
ECG	: Electrocardiography
EMG	: Electromyography
hEOG	: Horizontal Electromyography
vEOG	: Vertical Electromyography
tEMG	: Trapezius Electromyography
zEMG	: Zygomaticus Major Electromyography
BVP	: Blood Volume Pressure
GSR	: Galvanic Skin Response
RESP	: Respiration
EOG	: Electrooculography
BCI	: Brain Computer Interface
ERP	: Event Related Potentials
SAM	: Self-Assessment Manikin
IQR	: Interquartile range
HR	: Heart Rate
HRV	: Heart Rate Variability
VAD	: Valence Arousal Dominance
IAE	: Integral Absolute Error

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SUMMARY

Emotions play a critical role of humans' behaviors, beliefs, motivations and decisions. Affective computing is a promising area that receives a great deal of attention from researchers. It is heavily focused on the study and development of systems and devices that can recognize, interpret, process and simulate human emotions. Affective computing is an interdisciplinary working field that encompasses computer science, psychology, and cognitive science.

In this thesis, firstly, a background on emotion theories and the process of emotional experience in response to emotional stimulus are given. The literature review sheds light on existing studies on emotion recognition.

In order to develop emotion-aware systems, emotion related data of humans is required. Between publicly available affective databases for researchers, DEAP dataset is selected due to multi dimensional data characteristics and bodily responses of subjects, such as electroencephalography (EEG), electromyography (EMG), electrooculography (EOG), galvanic skin response (GSR), facial expression, while experimented people are watching music videos. Besides, DEAP also provides self-assessment ratings of subjects', after each video.

Fuzzy Cognitive Map (FCM) is a symbolic representation for the description and modeling of complex system. Different aspects in the behavior of a complex system are expressed with interacting concepts in fuzzy cognitive maps methodology.Fuzzy cognitive maps (FCMs) provide an extension of cognitive maps in which the links between the concepts represent the strength of impact with a fuzzy number. FCMs represent powerful cognition networks that use the synergy of fuzzy logic and neural network methodologies by employing causal relationships between concepts. In this thesis, FCMs are used as a modeling tool.

The analysis, modeling and evaluations in this thesis are divided into two parts: regression of emotional states and classification of emotions on arousal and valence scale. The construction and modeling of fuzzy cognitive map is done for both participant independent and participant dependent cases.

In conclusion part, performance of the constructed fuzzy cognitive map is discussed and difficulties in modeling are mentioned.

BULANIK BİLİŞSEL HARİTALAR YARDIMIYLA İNSAN DUYGULARININ MODELLENMESİ

ÖZET

Üretilen yazılımsal ve donanımsal sistemlerin insanların ihtiyaçlarına ve tercihlerine uyum sağlaması günümüzde oldukça önemlidir. Teknolojik gelişmeler ve bilimsel yenilikler sonucu içinde bulunulan yaşam şartları, bu sistemlerin adaptif olması kadar öngörü yapabilmesi gibi daha ileri seviye ihtiyaçlar doğurmuştur. Yine bu ihtiyaçlardan önemli bir tanesi, yazılımsal ve donanımsal sistemlerin insan duygularının farkında olması ve insanlardaki duygusal değişikliklere uyum sağlayabilmesidir. Farklı sektörler, verilen hizmetin kalitesini ve verimini artırmak için duygusal değişikliklerin farkında olan ve bu değişikliklere göre yeni eylem planı önerebilen sistemlerle ilgilenmektedir. Örneğin bir sinema filminin gösterimi boyunca insanlardaki duygusal değişimler ve bunların gösterilen sahne ile ilişkilendirilmesi film yapımcılarının ilgisini çekmektedir.

Duygular, insan davranışlarında, inançlarında ve kararlarında önemli rol oynarlar. Afektif hesaplama, son zamanlarda araştırmacıların ilgisini çeken ve gelecek vaadeden önemli bir alandır. Bu alan, yoğun olarak insan duygularını tanıyan, yorumlayan ve taklit edebilen sistemler geliştirmek üzerine çalışmalar yapmaktadır. Farklı birçok disiplinden araştırmacının katkı sağladığı bu alan daha çok bilgisayar bilimleri, psikoloji ve bilişsel bilimlerin kesişme noktasında bulunmaktadır.

Afektif hesaplama alanında çalışma yapabilmek için bu alanda insan duygularını oluşturan sinyalleri barındıran ve duygu durumlarının değerlendirildiği veritabanlarına ihtiyaç duyulmaktadır. Merkezi sinir sistemi, çevresel sinir sistemi, vücut hareketleri, bilgisayar-insan arabirimi kayıtları ile duygusal değerlendirme verileri barındıran bu veritabanları literatürde öne çıkan farklı ölçümleri ile birlikte yayınlanmaktadır. Verimli ölçüm yapmanın zorluğu ve deneyin tasarlanmasındaki zorluklar bu alanda yayınlanan veritabanlarının kullanımını artırmaktadır. Bu tez çalışması için araştırmacıların kullanımına açılmış birçok afektif veritabanı incelenmiş ve bunlar arasından DEAP veritabanı kullanılmak üzere seçilmiştir. Bu veritabanı, video klip izleyen insanlara ait fizyolojik sinyallerin (elektroensefalografi, elektromiyografi, deri geçirgenliği, yüz ifadeleri, kan basıncı ve sıcaklığı vb.) yanısıra izlenen videolar sonucu denekler tarafından öz-değerlendirme yöntemiyle toplanmış 5 farklı eksende duygusal durum verilerini (değerlik, uyarılma, baskınlık, tanıdık olma ve beğenme) barındırmaktadır.

Fizyolojik sinyallere ait bir dakikalık kayıtlardan, deneklerin öz-değerlendirme sonucu verdikleri oylara ulaşabilmek için giriş verisinde boyut indirgeme yapılması gerekmektedir. Öznitelik çıkarımı (feature extraction) yöntemleri ile bu sinyaller model girişi için tek bir değerle temsil edilir hale getirilmiştir. Örneğin parmaklardan alınan kan basıncı verisinden nabız ve nabzın değişimi bilgisi çıkarılır. Bütün 1 dakika boyunca nabız hızının maksimum değişimi önemli bir özniteliktir; çünkü

sempatik sinir sisteminin çalışması duygusal olarak uyarılmaya işaret eder. Yine yüzümüzde yer alan ve güldüğümüz zaman kasılan zygomaticus major kasından alınan elektromiyografi verisinin ortalama değerinin yüksek olması deneğin fazla güldüğüne işaret eder. Bütün deneklerde herbir sensörden alınan zamansal verilerden farklı tiplerde öznitelik çıkarılmıştır.

Öznitelik çıkarımı işlemleri ile birlikte farklı kanallardan elde edilen temel özniteliklerin, hedeflenen duygu durumları ile korelasyonları değerlendirilerek öznitelik seçimi aşaması gerçeklenmiş ve alt öznitelik kümeleri oluşturulmuştur. Bunun amacı, her özniteliğin duygunun oluşumda etkili olmaması ve farklı özniteliklerin çıkışa marjinal katkılarının aynı olması gibi durumlar sebebiyle kullanılmayacak özniteliklerin elenmesidir. Bu sayede hem hesaplama maliyeti azalmakta hem de oluşturulan modelin ezberlemesi engellenmektedir.

Veri hazırlama, makine öğrenmesinde önemli bir adımdır. İlk olarak çıkarılan öznitelikler,çıkışla korelasyonları dikkate alınarak elemeye tabi tutulup öznitelik seçme yöntemleri ile azaltılmış ve model oluşturulması için hazır hale getirilmiştir. Danışmanlı öğrenme yöntemi tercih edilerek, aynı girdiler için deneklerin puanlarının model tarafından tahmin edilen puanlarla farkının mutlak değerlerinin toplamı performans kriteri olarak seçilmiş, bu hatayı azaltmak üzerine model parametreleri değiştirilerek evrimsel bir optimizasyon stratejisi kullanılmıştır.

Modelleme amacıyla Bulanık Bilişsel Haritalar kullanılmıştır. Bulanık Bilişsel Haritalar, kompleks sistemleri modellemek için sembolik gösterim imkanı yaratan, bu sistemleri oluşturan bileşenlerin durumlarını birbirlerine olan etkileri ile birlikte ifade etme şansı veren önemli bir modelleme aracıdır. Herbir bileşenin konsept olarak isimlendirildiği, konseptlerin birbirlerine olan nedensel etkilerinin de bulanık sayılarla ifade edildiği bu araç, Bulanık Mantık ve Yapay Sinir Ağları yaklaşımlarının güçlü yanlarını barındırmaktadır. Bu tez kapsamında modelleme aracı olarak Bulanık Bilişsel Haritalar kullanılacaktır. Bir uzman tarafından veya bilgisayarlı hesaplama yöntemleri ile iki farklı şekilde oluşturulabilen Bulanık Bilişsel Haritalar, bizim durumumuzda uzman değil algoritma tarafından oluşturulmuştur. Haritaya ait parametrelerin aranması için Büyük Patlama Büyük Çöküş (Big Bang - Big Crunch) Eniyileme algoritması kullanılmıştır. Hızlı çözüm üretmesi ve hesaplama maliyetinin diğer birçok evrimsel algoritmaya göre düşük olması gibi yönleriyle tercih edilen bu algoritma ile performans kriterini iyileştirecek şekilde bulanık bilişsel haritaya ait ağırlıklar ve geçiş fonksiyonlarına ait eğim değerleri aranmıştır.

Bu tezde analiz, modelleme ve yorumlama kısımları iki parçadır: duygusal bileşenlerin regresyonu ve sınıflandırılması. Bu çalışmalar ise; katılımcı bağımlı ve katılımcı bağımsız olmak üzere iki durum için de gerçekleştirilmiştir. Regresyon çalışmasıyla hedeflenen belli fizyolojik girdiler kullanılarak modelin değerlik (valence) ve uyarılma (arousal) eksenlerinde değer üretmesi hedeflenmiştir. Sınıflandırma çalışmasında ise değerlik ve uyarılma eksenleri yüksek değerlik-düşük değerlik, yüksek uyarılma-düşük uyarılma şeklinde iki alt sınıfa bölünmüş ve fizyolojik girdilerle bu sınıfların tespit edilmesi hedeflenmiştir. Aynı duyguya olan fizyolojik tepkilerin ve öz-değerlendirme sonuçlarının kişiden kişiye değişmesi modellemede katılımcı bağımlı ve katılımcı bağımsız olmak üzere iki farklı yöntem izlenmesine yol açmıştır. Kişi bağımlı çalışma ile sadece o kişiye ait duygulanım süreci modellenmiş, kişiden bağımsız çalışma ile de bütün deney katılımcıları için modelleme yapılmıştır. Çalışmalar sonucu bulanık bilişsel haritaların duyguların modellenmesinde kullanılabilecek önemli bir modelleme aracı olduğu görülmüştür. Konseptlerin ve oluşturulan özniteliklerin psikolojik ve fizyolojik temellerle daha isabetli olarak belirlenmesi sonucu yapılan çalışmanın başarımının artacağı söylenebilir. Modellemede korelasyonla birlikte nedensellik yaklaşımının olması, psiko-fizyolojik bir sürecin nedensellik barındıran bir modelle ifade edilmesi yönüyle son derece önemlidir.

Bu tez kapsamında, ilk olarak duygu teorileri ve belli olaylar karşısında duygu oluşturan süreçleri incelemek için psikoloji ve fizyoloji alanında teorik altyapı sunulmuştur. Duygunun tanımı ve duygunun bileşenleri anlatılmıştır. Duyguların gösterilmesi ile ilgili kullanılan ayrık ve sürekli modeller tanıtılmış ve farklılıklarına değinilmiştir. Duyguların ifade edilebilmesi ve tespiti için kullanılan öz-değerlendirme (öz-raporlama) yöntemleri tanıtılmıştır. Bu anlamda, literatür taraması bölümü halihazırda yapılmış duygu tanıma çalışmaları hakkında bilgi vermektedir. Tezde kullanılan veri seti tanıtıldıktan sonra öznitelik çıkarımı ve öznitelik seçimi hakkında bilgi verilmiş ve çalışmada yapılan veri hazırlamanın detayları sunulmuştur. Modellemede kullanılan bulanık bilişsel haritalar hakkında detaylı bilgiye ve her bir modelleme çalışmasına detaylarıyla birlikte yer verilmiştir. Sonuç bölümünde, oluşturulan bulanık bilişsel haritalara ait sonuçlar ve modellemede karşı karşıya gelinen güçlüklerden bahsedilmiştir.

1. INTRODUCTION

This thesis describes the methods by which the emotional processes of humans were modeled and studied using Fuzzy Cognitive Maps (FCM). For the purposes of this research, a publicly available dataset, which is known as the DEAP dataset [4], was utilized. DEAP provides a comprehensive dataset of physiological responses, such as electromyograms, galvanic skin responses, respiration patterns, electroencephalograms etc., that were collected from subjects as they watched carefully selected movies. After watching these videos, the participants rated the videos in terms of arousal and valence levels. Through this self-assessment technique, DEAP aims to form a model that compares physiological signals with self-assessed arousal and valence levels.

Affective computing is a promising area that receives a great deal of attention from researchers. It is heavily focused on the study and development of systems and devices that can recognize, interpret, process and simulate human emotions. Affective computing is an interdisciplinary working field that encompasses computer science, psychology, and cognitive science. In order to study this field within a control engineering approach, it is necessary to know and understand the fundamental theories and models that are related to emotion within the context of psychology. Furthermore, it is important that students of affective computing know the meaning and purpose of the physiological measurements that can be used to analyze effects on emotions; in other words, that they understand the correlations between measurement features and the affect they have. Chapter 2 provides a brief overview of the emotion representation models that can be used for this purpose.

Fuzzy cognitive maps (FCMs) provide an extension of cognitive maps in which the links between the nodes (named concepts) represent the strength of impact with a fuzzy number. FCMs represent powerful cognition networks that use the synergy of fuzzy logic and neural network methodologies by employing causal relationships between concepts. In this study, FCMs are used as a modeling tool. Chapter 3 provides detailed information about FCMs. The parameters of the fuzzy cognitive map are determined by using a supervised learning technique. As a learning procedure, the Big Bang Big Crunch Learning Algorithm is used. This algorithm originated from Big Bang Big Crunch Optimization Algorithm and further information about this formula is also provided in Chapter 3.

The DEAP dataset is formally introduced in Chapter 4. The main parts of the data preparation phase, which feature extraction and feature selection, are explained in full before the discussion progresses to examine how. After the preparation of the learning data, in Chapter 5, the fuzzy cognitive map structure is employed for modeling purposes. Finally, Chapter 5 concludes with an overview of the experimental results acquired during this study.

Chapter 6 presents the conclusion to the thesis and provides a basic examination of the success of the study together with recommendations for future works.

1.1 Purpose of Thesis

An important area of technological development concerns the way in which software and hardware systems can be adapted to human behaviors and preferences. Increasing computation power and decreasing the cost of computation and storage allows us to store more data about human interactions and adapt offerings to users' behaviors. The extraction of usage patterns from human interactions in order to adapt technology to users' preferences represents an important area of study, and the techniques developed through this type of research are widely used in marketing and advertising applications, recommendation systems and decision support classifications, etc.

The adaptation of technology to both the ways in which users interact with hardware and software and the emotional responses that computer systems elicit, represents a promising field of development. Affective computing aims to narrow the gap between human emotions and automated systems. Emotion-aware systems are becoming increasingly popular on a daily basis as a result of the enhancements that are available in the affective computing area.

Emotion is a psycho-physiological process or mental state that is triggered by conscious and/or unconscious perception of an object or situation; it is often associated with motivation, personality and disposition, mood and temperament [4,5]. Emotions play a critical role in human communication and interaction. Furthermore, it is generally accepted that humans operate under the influence of their emotional states while they are thinking, making decisions and responding to situations, etc. Hence, it is important that technologists develop systems that are capable of adapting to human emotions.

Various models for representing different emotional states are described in current literature. These models are categorized as discrete emotion models and continuous emotion models. As a result of the difficulties associated with understanding the meaning of a word across different cultures and languages, the continuous representation model was employed for the purposes of this study and Thayer's Emotion Model in particular was used in order to classify emotions according to levels of valence and arousal.

Emotion modeling/forecasting is a promising and attractive research area that is attracting an increasing amount of attention from notable researchers. Existing studies appear to favor methods of determining emotions that hinge on physiological responses such as EEG and EMG. Using a number of techniques, such as statistical methods, neural networks and support vector machines, various studies have provided comprehensive models of human emotions. This thesis concentrates on one such model: fuzzy cognitive maps.

Fuzzy cognitive map is used as a modeling tool that can be used to examine the strength of impact of the relationship between elements of a mental landscape in order to identify, examine and analyze causality of change in psycho-physiological processes. The basic motivation behind this study was to aid the future development of methods, such as machine-learning techniques, that could be used to explain the causality of psycho-physiological processes.

1.2 Literature Review

The purpose of this study is to forecast and model human emotions. The thesis is formed of two main sections. The first section examines the existing literature that is available on the psychological and psycho-physiological nature of human emotions. The second section contains a literature review of the current models that are used to examine, recognize and forecast emotions and the causes of such emotions.

1.2.1 Emotion representation

There are many models in existence that attempt to provide a representation of emotions. These models can be separated into two types: discrete and continuous models. Discrete Emotion Models are based on the expression of different feeling states with different words. The discrete emotion theory presented in existing literature often classifies emotions into discrete categories. For example, six basic emotions were initially proposed by Ekman and Friesen [6] before being recast as primary-, secondary- and tertiary-level emotions by Ekman at a later date. Ant and Plutchik [7] also suggested a discrete emotion model. However, one of the main problems associated with the discrete models concerns the fact that emotions are perceived and expressed differently within the context of different regions, countries or cultures and this makes such classifications questionable [8].
The continuous emotion model involving the feelings of arousal and valence was proposed by Russell and within his model emotions are divided by two different axis. In 1989 Thayer introduced a similar model in which he described how 12 different emotions lie on a Cartesian coordinate system. [9]

1.2.2 Emotion recognition

A large number of theorists have turned their attention to emotion modeling in recent years and existing studies can be separated into two broad groups: those that are based on the bodily signals that humans exhibit in response to emotional stimulus and those that extract the features of contents (audio-visual content) that trigger emotions.

Some of the studies described in the existing literature provide models for forecasting human emotion through the activation of different regions of the brain at different frequency bands using EEG. Brain-computer interface technologies that use the electrical signals of the brain are commercially available. One example of such an application is the Emotiv system is shown at Figure 1.1.

Figure 1.1: Emotiv headset, retrieved from [75]

With the exception of EEG, it is possible to collect bodily response data that provides clues about an individual's emotional status. For example, information about the emotions that an individual is experiencing can be gleamed through examining various physiological aspects:

- behavior of their muscles (EMG),
- blood pressure (BVP)
- galvanic skin response (GSR)
- heart (ECG), and
- through measuring respiration.

There are a number of products available on the market that specialize in the use of physiological signals to forecast emotional state. One such product is the QSensor.

Some studies use image-processing techniques to examine the ways in which facial expressions are reflective of emotions. For example, an individual's pupil dilation and eye gaze provide important clues regarding the measurement of attention.

In addition to modeling emotions via measurements taken from the human body, there are also studies in existence that tag and categorize the contents of audio-visual content via feature extraction methods. For example, the decomposition of audio content to speech, music and environmental sounds; decomposition of visual content to lights and visual excitements [10]. In addition to this, some studies have attempted to extract emotion-category-specific features, named audio-visual words, whereby emotion recognition made by feature words by latent topic model. With the help of these studies, the impact of audio-visual contents can be predicted by analyzing the multimedia contents' features.

Many different techniques for modeling emotions have been presented in the literature. These studies involve classification and regression studies and can be classified into two groups: participant dependent [11, 12] and participant independent [13–16].

In these studies, it is possible to study both classification and regression using different techniques, including linear discriminant analysis [12, 16], K-Nearest-Neighbour (KNN) [13, 16], Back Propagation (MBP) [13], pseudoinverse Linear Discriminant Analysis (pLDA) [15], emotion-specific multilevel dichotomous classification [15], radial basis function networks (RBFN) [16], a Quadratic Discriminant Analysis (QDA) [16], Multilayer Perceptron (MLP) [16] and Support Vector Machine (SVM) [11, 14].

Salmeron proposed the use of FCMs as a means of forecasting emotional behavior; however, his paper did not constitute an empirical study and only discussed the idea of using FCMs for the purposes of emotion forecasting at a high level [1]. In his study, Salmeron [1] said that specific emotion can be labeled using Thayer's Emotion Model.

As far as the authors of the current study are aware, there is no research in existence that has formally attempted to model or forecast emotions by applying FCM to a specific dataset.

2. PSYCHOLOGICAL AND PHYSIOLOGICAL BACKGROUND

2.1 What Exactly Are Emotions?

Defining emotions is a notorious problem. The answer to the question: "What exactly are emotions?" strongly depends on the theoretical approach that is applied [17]. Emotions can be considered to be complex phenomena that encompass both subjective and objective factors that consist of affective, cognitive, conative and physiological components:

- Affective: the subjective experience of situations that are connected to feelings of arousal, pleasure or dissatisfaction.
- Cognitive: the perception and evaluation of the emotional situation.
- Conative component : expressive behavior that includes facial expressions, body gestures and any other actions that provide a preparatory function for action in response to an emotional
- Physiological: peripheral reactions of the body, which are mediated by the autonomous nervous system (physiological arousal). These include phenomena such as blushing and changes in respiration, perspiration and heart rate.. . .

Darwin argues that the sole purpose of emotions is to aid survival and, as such, they should be observable in both human and animals [18]. James [19] formulated the idea that emotions have certain peripheral physiological responses. He claimed that humans experience emotions as a direct result of changes in physiological responses. However, social constructionists disagree with this view and claim that emotions are simply the results of social interactions and responses to cultural rules. The Darwinian theory of emotion emphasizes the evolution of the history of the species and concentrates on the effect that emotions have on survival. Social constructionists emphasize the history of individuals in generating similar bodily responses to emotions [18].

A number of theories have been developed with the intention of defining emotion in terms of the aspect of cognition. One popular cognitive theory on emotion is appraisal theory. According to appraisal theory, cognitive judgment or evaluation of the situation is the most important point in the appearance of emotions [20–22].

According to Orthoney, Clore and Collings [21] the first part of the emotion occurrence is perception of an event, object or an action. After this perception, an evaluation of the events, object or an action according to personal wishes and norms follows. During the process by which an individual appraises an emotional experience, the viewer investigates events, situations and objects in the context of subjective novelty, pleasantness, goal, attainability, copability and compability with his/her norms. Finally, perception and evaluation forms a specific emotion that changes physiological responses, motor actions and feelings.

Although many theorists prefer to see emotion and cognition as two independent but interacting systems, the cognitive theory works on the assumption that the component process model of emotions accepts emotion as a cognitive process. Scherer defines emotion as "an episode of interrelated, synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism" [20]. These components are cognitive (appraisal), neurophysiological (bodily symptoms), motivational (action tendencies), motor expression (facial and vocal expression) and subjective (emotional experience).

Many affective phenomena, such as preferences, feeling, mood and attitudes, can be distinguished from one other with the help of the components suggested by Scherer [20]. For example, Scherer makes an important distinction between emotion and mood. Mood is long term, slow moving and not dependent on a specific object or stimulus; on the other hand, emotion occurs over a very short time frame compared to mood.

2.2 How Can We Measure Emotions?

There is no single standard method that can be used to measure emotion. It is only through a stable measurement of all the component changes involved that a generic measure of an emotion can be achieved. This means that, in order to measure emotion in an ideal world, we would need to measure (1) the continuous changes in appraisal processes at all levels of the central nervous system processing; (2) the response patterns generated in the neuroendocrine, autonomic, and somatic nervous systems; (3) the motivational changes in particular action tendencies (including the neural signatures in the respective motor command circuits); (4) the patterns of facial and vocal expression as well as body movements; and (5) the nature of the subjectively experienced feeling state that reflects all of these component changes. Given the complexity of achieving all these factors, it can be argued that it is impossible to measure emotion and that it is unlikely that an accurate measurement will become standard procedure. However, various techniques have been developed in order to measure each of the components such as appraisal [17, 23], brain mechanisms [24], physiological response patterns [25] and expressive behavior [26].

2.2.1 Emotional representations

Various emotion categorization methods have been proposed so far. They can be described as either discrete models or continuous models.

2.2.1.1 Discrete models

Discrete emotions are inspired by Darwin and support the idea that a number of basic and universal emotions exist [17,18]. Darwin suggested that emotions are fundamental to a species' survival. Different psychologists have proposed various types of "basic emotions" in the literature. One example of a theory of basic emotions is that of the six universal basic emotions that was proposed by Ekman and Friesen [6]. These are represented by the facial expressions associated with surprise, anger, happiness, sadness, fear and disgust and they are the same among different cultures and countries. (Figure 2.1) It is important to note that four of them are negative.

Figure 2.1: Six Universal Emotions, retrieved from [76]

Ekman expanded this list with some additional emotions: amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure and shame [27].

W.G. Parrot proposed a tree structure of primary, secondary and tertiary emotions [28], with the primary emotions being love, joy, surprise, anger, sadness and fear. (Figure 2.2)

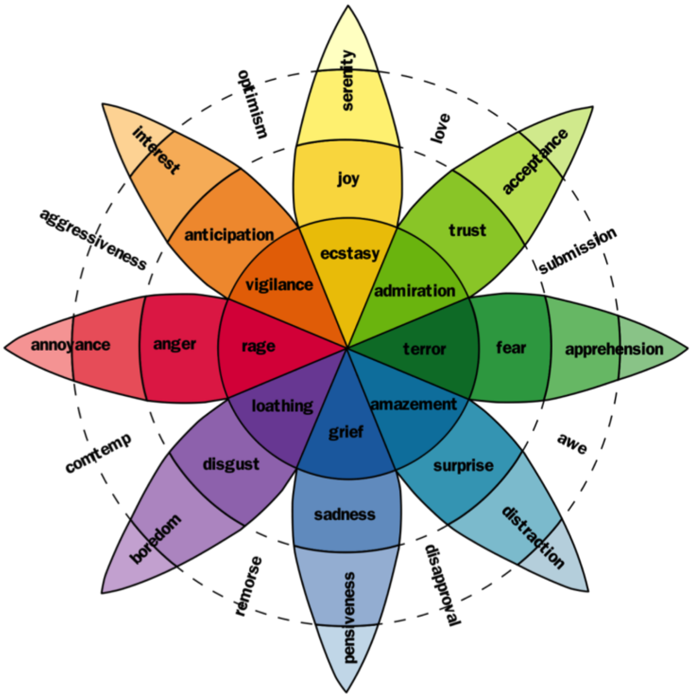

Figure 2.2: Plutchik's Wheel of Emotions, retrieved from [77]

Plutchik proposed eight primary emotions. These were anger, fear, sadness, disgust, surprise, anticipation, trust and joy. He also stated that basic emotions are biologically primitive and have evolved in order to increase the reproductive success of animals [7]. Within his theories he distinguished between primary, secondary and tertiary emotions and suggested an emotion wheel and conical version of this model that could be used to examine the relationships between these different types of emotions.

2.2.1.2 Continuous models

It is widely recognized that it is difficult to represent discrete emotions. The main problem being that emotion names are not cross lingual: the names do not have direct translations in different languages. For example "disgust" does not have an exact translation in Polish [29]. Wundt [30] was the first to propose a dimensional continuous representation for emotions. This approach suggested that emotions can be represented as points in a continuous space and that discrete emotions are folk-psychological.

Psychologists often represent emotions in an n-dimensional space that is generally 2 or 3 dimensional. There are common dimensional spaces. These originate from cognitive theory and are widely used. Examples include the 3D valence-arousal-dominance (VAD) and the pleasure-arousal-dominance (PAD) space. The valence scale ranges from unpleasant (sad, stressed) to pleasant (happy, elated). The arousal space ranges from passive (uninterested, bored) to active (alert, excited). The dominance scale ranges from submissive (without control) to dominant (in control). Fontaine et al. [31] suggested one more dimension: predictability to PAD space. This dimension (predictability) describes the extent to which the sequence of events is predictable or surprising for a person.

Russell proposed the arousal-valence space, which is the theory that is most commonly applied within emotion studies. An example of arousal valence scale is shown at Figure 2.3

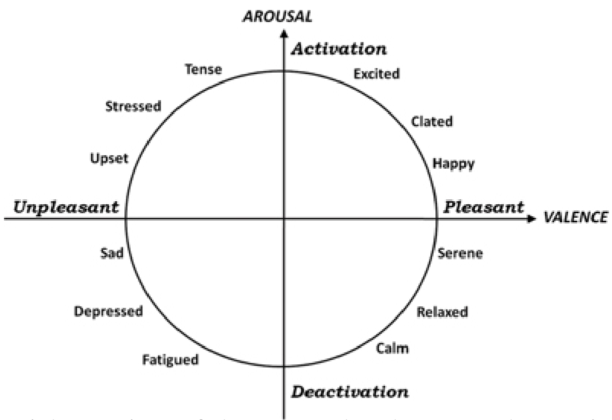

Figure 2.3: An iIlustration of the arousal-valence scale, retrieved from [78]

Thayer [9] proposed a model that contains a unit circle on a Cartesian coordinate system which is shown at Figure 2.4. The Thayer's emotion model is frequently used to avoid the ambiguity of adjectives. The emotion classes are divided into four quadrants and each quadrant has three emotion labels. The first quadrant, positive valence and positive arousal, is composed of three emotions: pleased, happy and excited. The second quadrant, positive arousal and negative valence, contains the emotions of annoyed, angry and nervous. The third quadrant, negative arousal and valence, contains the emotions of sad, bored, sleepy and finally the fourth quadrant is composed of calm, peaceful and relaxed.

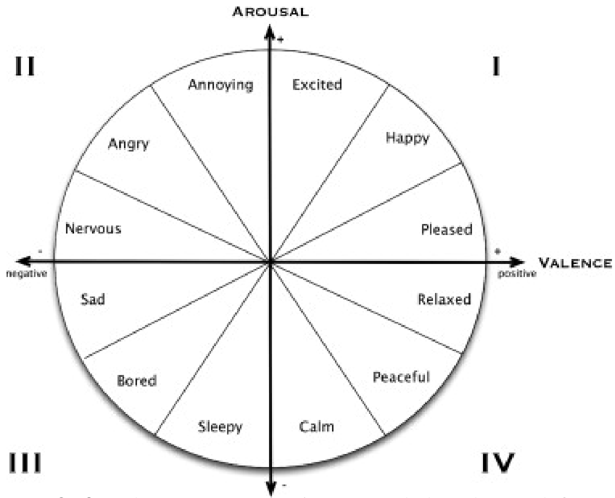

Figure 2.4: Thayer's Emotion Model, adapted from [1]

2.2.2 Emotional self-reporting methods

Emotion experimental participants can find continuous models of emotions to be difficult to understand and accurately determining the emotional state of a subject during an experiment represents a challenge for psychologists. Various methods of emotional self- reporting are presented in the literature [17, 32–35].

One such tool is the Self-Assessment Manikin (SAM). This specifies that for each of the valence, arousal and dominance dimensions there are a series of manikins that can be used to visualize the different strength along the axes. Participants select the manikin at each dimension that most closely expresses the emotion they are experiencing. (Figure 2.5)

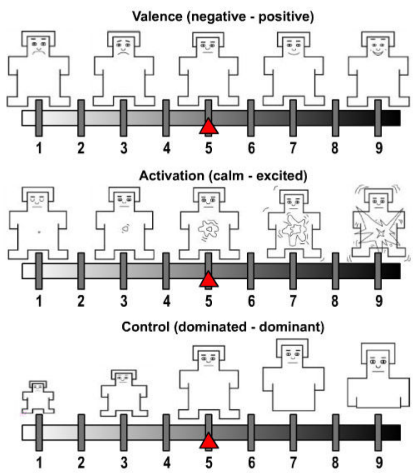

Figure 2.5: Self-Assesment Manikins, retrieved from [79]

Another Self-Reporting tool is the Geneva Wheel (GEW) [17], which was proposed by Scherer. The Geneva wheel (Figure 2.6) is composed of 16 emotions that are positioned around a circle. The emotions included in the wheel combine both dimensional and discrete emotional approaches. Each emotion around the wheel incorporates five circles that increase in size from the center to the outer edges.

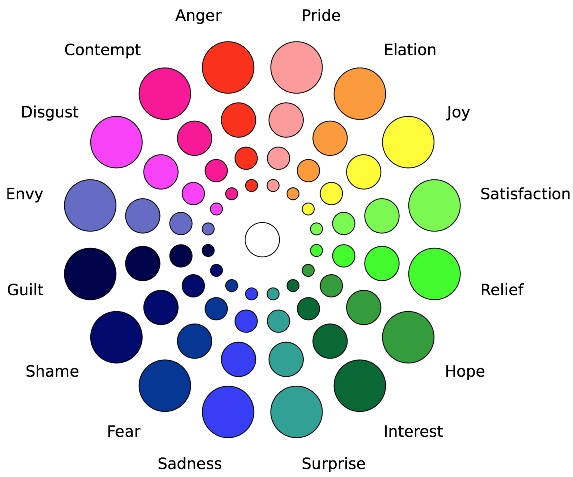

Figure 2.6: Geneva emotion wheel, adapted from [2]

2.2.3 Bodily signals and sensors

Physiological activity is an important component of an emotion [22, 36]. Humans respond to stimuli by their facial expressions, bodily gestures and physiological responses. Here is a brief explanation of the bodily signals and sensors provided.

2.2.3.1 Electromyography (EMG)

An EMG signal is the electrical potential that is generated by the electrical or neurological activation of muscle cells. EMG can be recorded by attaching electrodes to the area of skin that covers the muscles associated with a given emotion or condition. A pair of electrodes attached along the muscles record the difference of the electrical potential between two points.

Facial expressions and body movements cause the activation of different muscles. The muscular activity related to emotional responses can be measured using electromyography. For example, zygomaticus major activates while smiling and frontalis muscles activate when an individual experiences attention and stress [37]. Head movements activate the trapezius muscle.

2.2.3.2 Galvanic skin response (GSR)

Galvanic skin response (GSR), also known as skin conductance (SC), electrodermal response (EDR), psychogalvanic reflex (PGR) or skin conductance response (SCR), is a physiological signal that measures electrical conductance or resistance between two points on the skin. Skin conductance changes with moisture, which is produced by sweating. Sweat glands are under the control of the sympathetic nervous system and their activity changes according to the level of an individual's emotional arousal [38]. The mean value of GSR is related to the level of this arousal.

2.2.3.3 Electrocardiography (ECG) and blood volume pulse

Blood Volume Pulse (BVP) is the volume of blood in the peripheral vessel and can be measured by photoplethysmograph or plethysmograph. The volume of the blood is measured using an infrared emitter and detector that is placed on the skin. BVP signals are usually taken from the subject's finger.

An important property of the BVP signal is that it is possible to derive an individual's heart rate by counting the peaks. BVP also provides a relative measure of pressure in the blood and, as such, its level can provide an indirect measure of blood pressure.

Because of the nature of muscular activity, heart muscle activity generates an electrical potential difference on the skin. An electrocardiogram (ECG or EKG) is an electrical recording of the heart. Electrodes that are used for the measurement of the heart muscle activity are placed on the chest. Signal heart rate (HR) and heart rate variability (HRV) can be detected from an ECG. HR and HRV are related to emotions. For example, pleasant stimuli can increase an individual's heart rate and HRV decreases with fear, sadness and happiness [39].

2.2.3.4 Respiration

Respiration depth or amplitude can be measured by calculating the expansion of the chest or abdomen circumference. From the signal generated by a respiration belt, respiration rate and depth can be determined. Different emotions result in different respiration patterns. Relaxation causes slow respiration and high arousal, such as anger or fear, causes irregular rhythm and quick variations [15, 39].

2.2.3.5 Skin temperature

Different emotional states result in changes in the temperature of the skin [40]. It is necessary to say that temperature changes slowly. Skin temperature is measured by placing a sensor on the subject's finger.

2.2.3.6 Electroencephalography (EEG)

Electroencephalography (EEG) is a non-invasive technique that is used to measure brainwaves. Traditionally, EEG measurements have been used to diagnose medical conditions such as epilepsy. EEG signals are recorded through electrodes that are placed on the scalp (Figure 2.7). Electrode gel is applied to the scalp in order to promote conductivity before a cap with integrated electrodes is placed on the head.

Figure 2.7: EEG cap, retrieved from [80]

Electrode locations are determined according to an international standard named 10-20 system (Figure 2.8).

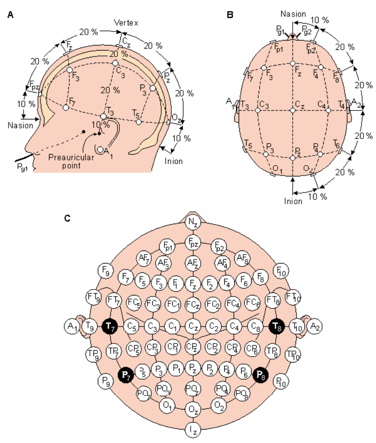

Figure 2.8: 10-20 System, retrieved from [81]

The analysis of EEG signals for brain-computer interfaces (BCI) mainly focuses on event-related potentials (ERPs) or spectral-power features. A table that provides an overview of frequency bands is provided below (Table 2.1).

Table 2.1: An overview of brainwave frequency bands in healty persons.

Name	Band	Description
δ-waves	0-4Hz	Occur in infancy and adult deep sleep.
θ-waves	4-7Hz	Occur in children, can indicate drowsiness, idling or emotional stress.
α-waves	7-12Hz	Occur in adults during relaxation and/or closing the eyes. Mostly occur in the occipital region.
μ-rhythm	7-12Hz	Activity occurring in the α range. Measured over the sensorimotor cortex and attenuates with limb movement.
β-waves	12-30Hz	Associated with active concentration, thinking. Attenuated with limb movement.
γ-waves	30-100Hz	Associated with high-level mental processing.

3. FUZZY COGNITIVE MAPS AND LEARNING

Dynamic systems create important difficulties for decision makers because modeling a dynamic system can be hard to achieve in a computational sense. In addition, the formulation of a mathematical model may be difficult, sometimes impossible. Formulating a mathematical model has several drawbacks. The first of these concerns the fact that developing the model typically requires a great deal of effort and specialized knowledge outside the domain of interest. As a second drawback, if the system contains a feedback loop this can cause casual influences in complicated chains to be nonlinear, in which case a quantitative model may not be possible. Finally, numerical data may be hard to come by or uncertain.

Natural language arguments in the absence of formal models are required in order to understand and express the system. FCMs provide an alternative qualitative approach to dynamic systems. FCMs were first proposed by Kosko and originated from cognitive maps.

3.1 Cognitive Maps

A political scientist Axelrod [41] introduced cognitive maps in the 1970s for representing social scientific knowledge and describing the methods that are used for decision making in social and political systems. These maps indicates the crisp cause-effect relationships that are perceived to exist among the elements of a given environment. They appear as signed diagraphs that contain nodes called concepts and edges, which signify causal connections.

In a cognitive map a positive link from Concept A to Concept B means A casually increases B; a negative link from Concept A to Concept B means A causally decreases B. Cognitive maps facilitate documentary coding and allow researchers to construct symbolic representations of expert documents. A cognitive map constructed from Henry A. Kissinger's article [3] is shown at Figure [**?**].

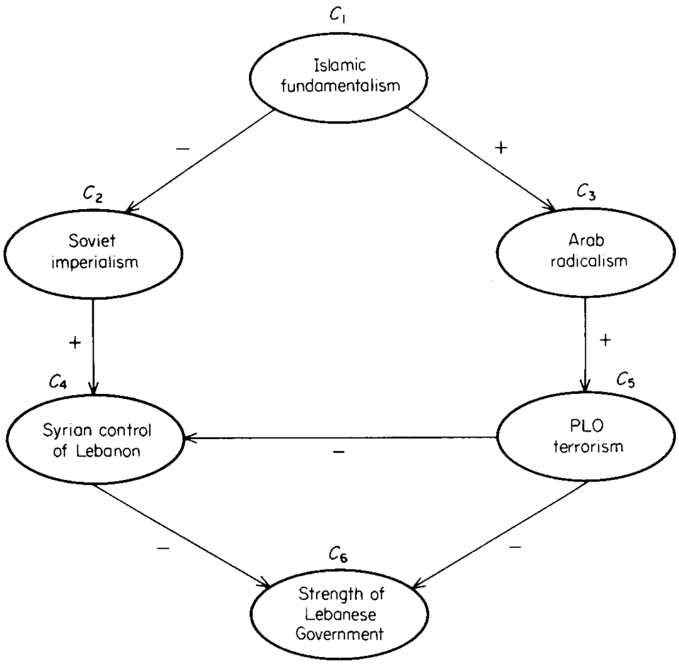

Figure 3.1: A cognitive map constructed from Henry A. Kissinger's article [3]

Axelrod suggested a matrix representation named the adjacency matrix of cognitive maps. Casual relationships in cognitive maps can be defined and represented using adjacency-matrix components (Table 3.1).

Table 3.1: Adjacency matrix representation

$$W = \begin{array}{c} \\ c_1 \\ c_2 \\ c_3 \\ c_4 \\ c_5 \\ c_6 \end{array} \begin{array}{c} \begin{array}{cccccc} c_1 & c_2 & c_3 & c_4 & c_5 & c_6 \end{array} \\ \begin{pmatrix} 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array}$$

3.2 Fuzzy Cognitive Maps

Kosko [3, 42] enhanced the power of cognitive maps considering fuzzy values for the concepts of the cognitive map and fuzzy degrees of interrelationships between concepts. In general, causality between concepts are fuzzy; its influence may be minor, major or somewhere in between, or it occurs regularly, irregularly etc. "More general still, the knowledge-base building promise of cognitive maps is combining knowledge sources' cognitive maps, but the fuzziness of the combined knowledge rises to the level of fuzziness of the fuzziest knowledge source" [3]. This knowledge-base building property is provided by FCMs. A fuzzy cognitive map for bridge target value is shown at Figure 3.2.

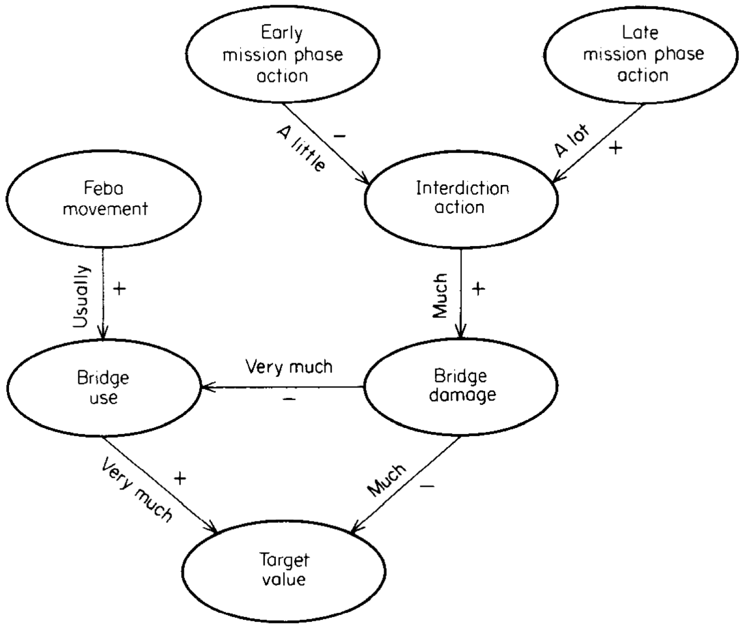

Figure 3.2: A fuzzy cognitive map for bridge target value with fuzzy causal relationships [3]

FCMs are fuzzy signed directed graphs with feedbacks that illustrate the cause and effects between the various concepts represented in a system. [43] A map consists of concepts and their causal relationships according to perceived states and the events of the environment. The value of a node states the degree to which the concept is active in the system at a particular time. This value is a function of the sum of all input links multiplied and the value of the source concept within the immediately previous state. The threshold function applied to the weighted sums can be fuzzy in nature. Moreover, concept values are expressed on a normalized range denoting a degree of activation rather than an exact quantitative value. These facts of FCMs are taken from the fundamentals of fuzzy logic. The threshold function serves to reduce unbounded inputs to a strict range.

The fuzzy indicates that FCMs are often comprised of concepts that can be represented as fuzzy sets and the causal relations between the concepts can be fuzzy implications, conditional probabilities. A directed edge W_{jk} from concept W_j to concept W_k. In simple FCMs directional influences take on trivalent values. There are -1,0, +1, where -1 indicates a negative relationship, 0 no causality relationship and +1 a positive relationship. In general, edge values are in the interval of [-1,1]:

- $W_{jk} > 0$ indicates direct (positive) causality between concepts W_j and W_k. That is, the increase (decrease) in the value of W_j leads to the increase (decrease) of W_k.
- $W_{jk} < 0$ indicates inverse (negative) causality between concepts W_j and W_k. That is, the increase (decrease) in the value of W_j leads to the decrease (increase) on the value of W_k.
- $W_{jk} = 0$ indicates no relationship between W_j and W_k.

A Fuzzy Cognitive Map F consists of 4-tuple (N,W,C,f) [44] where,

- N = $N_1, N_2, \ldots, N_n$ is the set of nodes, namely concepts of the graph.
- E : $(N_i, N_j) \rightarrow w_{ij}$ is a function of N x N to K associating w_{ij} to a pair of concepts (N_i, N_j), with w_{ij} denoting a weight of directed edge from N_i to N_j, if $i \neq j$ and e_{ij} equal to zero if i = j. Thus $W(NxN) = (w_{ij}) \in \mathrm{K}^{\mathrm{nxn}}$ is a connection matrix.
- C: $N_i \rightarrow C_i$ is a function that at each concept N_i associates the sequence of its activation degrees such as for t $\in$ N, $C_i(t) \in$ L given its activation degree at the moment t. C(0) $\in \mathrm{L}^{\mathrm{n}}$ indicates the initial vector and specifies initial values of all concept nodes and C(t) $\in \mathrm{L}^{\mathrm{n}}$ is a state vector at certain iteration t.
- f: R $\rightarrow$ L is a transformation function, which includes recurring relationship on $t \geq 0$ between C(t+1) and C(t).

Functional model of FCM is described by the Equation 5.1, which is used to perform simulations of the system dynamics. Simulation includes the computing state of the system, which is described by a state vector, over a number of successive iterations.

$$C_j(t+1) = f\left(\sum_{\substack{i=1 \\ i \neq j}}^{n} C_i(t) w_{ij}\right) \qquad \textbf{(3.1)}$$

The state vector defines current states (values) of all concepts (nodes) in a particular iteration. The value of a given node is calculated from the previous iteration values of nodes, which impacts the given concept through a cause-effect relationship (nodes that are connected to the given node).

The transformation function is used to limit the weighted sum to a certain range, which is usually set to [0,1]. The normalization hinders quantitative analysis but allows for comparisons between nodes, which can be defined as active (value of 1), inactive (value of 0) or active to a certain degree (value between 0 and 1). The four most common transformation functions are as follows:

- bivalent

$$f(x) = \begin{cases} 0, & \text{if } x \leq 0 \\ 1, & \text{if } x > 0 \end{cases} \tag{3.2}$$

- trivalent

$$f(x) = \begin{cases} -1, & x \leq 0.5 \\ 0, & -0.5 < x < 0.5 \\ 1, & x \geq 0 \end{cases} \tag{3.3}$$

- logistic

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{3.4}$$

- hyperbolic tangent

$$f(x) = tanh(\lambda x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}} \tag{3.5}$$

Where λ determines the slope of the sigmoid and hyperbolic tangent function.

Applying the discrete-output transformation function (bivalent or trivalent function), the simulation heads to either a fixed state vector value, which is called hidden pattern or fixed point attractor, or keeps cycling between a number of fixed state vector values, which is known as a limit cycle. Using a continuous-output transformation function (e.g. sigmoid function), the fixed-point attractor and limit cycle, as well as so-called chaotic attractor can appear.

3.3 Development of Fuzzy Cognitive Maps

In practice, two approaches to the development of FCMs are used: manual and computational. [45] Most, if not all, of the reported models were developed manually by domain expert(s) and are based on expert knowledge in the area of application. The experts manually design and implement adequate models according to their mental understanding of the modeled domain.

Three main steps constitute this process [46]:

1. Identification of the key domain issues or concepts.
2. Identification of casual relationships among these concepts.
3. Estimation of the strengths of causal relationships.

The first two steps, which result in establishing an initial draft of the FCM model, include the identification of concept nodes and the relationships among them are represented by edges. This is performed manually using pencil and paper by taking advantage of FCM's graph representation. However, the main difficulty associated with this process concerns accurately establishing the weights (strength) of the defined relationships. In order to achieve this, the following procedure might be used [43, 46]:

1. The influence of one concept on another between each pair of concepts is determined as "negative", "positive" or "none."
2. All relationships are expressed in fuzzy terms, e.g. weak, medium, strong and very strong.
3. The established fuzzy expressions are mapped to numerical values, most frequently to the range from 0 to 1; For example, weak is mapped to 0.25, medium to 0.5, strong to 0.75 and very strong to 1.0.

In general, the manual procedures for developing FCMs have a number drawbacks. They require an expert who has knowledge of the modeled domain and, at the same time, knowledge of the FCMs formalism. Since even medium size models involve a large number of parameters, i.e. weights, it is often very difficult to obtain satisfactory performance.

These problems led to the development of computational methods for learning FCM connection matrix, i.e. casual relationships (edges) and their strength (weights) based on historical data and a computational procedure that is able to automatically compute the connection matrix. A number of algorithms for learning the model structure of FCMs have been proposed. These proposed methods can be summed in three groups named Hebbian-type learning methods, population-based (evolutionary) learning methods and hybrid learning algorithms [47].

A simple differential Hebbian learning law (DHL) for FCM is stated in [48]. This has been extended in [49] as a balanced differential learning algorithm for FCM. Further extensions, called nonlinear Hebbian learning (NHL) and Active Hebbian learning algorithm (AHL) are presented in [50] and [51], respectively. An improved version of the NHL method named data driven NHL (DDNHL) is proposed in [52]. Another study to train a FCM is proposed in which a new model for unsupervised learning and reasoning on a special type of cognitive maps that are realized with Petri nets [53]. All Hebbian-type learning methods have the goal to learn the connection matrix with single historical data set.

Rather than Hebbian-type learning methods, population-based learning methods are more in demand. The learning goal of population-based methods can be connection matrix with optimal weights or matching input pattern. Obtaining the connection matrix with optimal weights will lead FCM to its desired activation state values for each concept. Population based learning algorithms with connection matrix goal of learning that are recently studied can be listed as: Particle Swarm Optimization (PSO) [54], Genetic Strategy (GS) [55], Real-coded Genetic Algorithm (RCGA) [45], Simulated Annealing (SA) [56], tabu search [57], immune algorithm [58], Big Bang-Big Crunch (BB-BC) optimization algorithm [59], Extended Great Deluge Algorithm (EDGA) [60], Artificial Bee Colony (ABC) algorithm [61].

The hybrid learning methods are implemented by combining the first two mentioned learning types (Hebbian-based learning (HL) and the population-based learning) for FCMs. There are two hybrid algorithms studied, one has combined NHL and differential evolution (DE) [62] and the other algorithm has combined RCGA and NHL algorithms [63]. The learning goals of these two the hybrid learning methods are the connection matrix and they use single historical data set.

3.4 Big Bang - Big Crunch Optimization Algorithm

The Big Bang - Big Crunch (BB-BC) optimization algorithm inspired one of the theories of the evolution of the universe; namely, the Big Bang and Big Crunch Theory [64]. It was first proposed as a new optimization method in 2006 and was shown to be capable of quick convergence. BB-BC has a high performance on multimodal fitness functions like Ackley Function and Rastrigin Function [64]. The BB-BC algorithm can be designed to take into account partial search space. The BB-BC algorithm is capable of limiting search space by defining some constraints on parameters and produces solutions in this limited space in an efficient way.

The Big Bang-Big Crunch (BB-BC) optimization method is constructed in two main steps. The first step is the Big Bang phase, where candidate solutions are randomly distributed over the search space. The next step is the Big Crunch where a contraction procedure calculates a center of mass for the population. The initial Big Bang population is randomly generated over the entire search space just like the other evolutionary search algorithms. All subsequent Big Bang phases are randomly distributed about the center of mass or the best fit individual in a similar fashion. The working principle of this evolutionary method involves the transformation of a convergent solution to a chaotic state, which is a new set of solutions. The procedure of the BB-BC optimization is given in the table below:

Step 1 (Big Bang Phase)

N candidates are generated randomly in the search space.

Step 2

The cost function values of all the candidate solutions are computed.

Step 3 (Big Crunch Phase)

The center of mass is calculated. Either the best fit individual or the center of mass is chosen as the point of Big Bang Phase.

Step 4

New candidates are calculated around the new point calculated in Step 3 by adding or subtracting a random number whose value decreases as the iterations elapse.

Step 5

Return to Step 2 until stopping criteria has been met.

After the Big Bang, a contraction procedure is applied during the Big Crunch. During this phase, the contraction operator takes the current positions of each candidate solution in the population and its associated cost function value and computes a center of mass. The center of mass can be computed as:

$$x_c = \frac{\sum_{i=1}^{N} \frac{1}{f^i} x_i}{\sum_{i=1}^{N} \frac{1}{f^i}} \quad \textbf{(3.6)}$$

where x_c = position of the center of mass; x_i= position of candidate; f_i = cost function value of candidate i; and N = population size.

Instead of the position of the center of mass, the best fit individual can also be chosen as the starting point in the Big Bang phase.

The new generation for the next iteration Big Bang phase is normally distributed around x_c.

$$x_i^{new} = x_c + \sigma \quad \textbf{(3.7)}$$

where x_i^{new} = the new candidate solution i; and σ standard deviation of a standard normal distribution. The standard deviation decreases as the iterations elapse according to the following formula:

$$\sigma = \frac{r\alpha(x_{max} - x_{min})}{k} \quad \textbf{(3.8)}$$

where r is random number; α is a parameter limiting the size of the search space, x_{max} and x_{min} are the upper and lower limits; and k is the number of the iterations.

Therefore, the new point is generated as follows:

$$x_i^{new} = x_c + \frac{r\alpha(x_{max} - x_{min})}{k} \quad \textbf{(3.9)}$$

Since normally distributed numbers can exceed ± 1, it is necessary to limit the population to the prescribed search space boundaries. This narrowing down restricts the candidate solutions into the search space boundaries.

4. DATA PREPARATION

4.1 Affective Databases

In this thesis, emotion modeling with bodily responses has been studied. In order to develop a model on a real world data, several databases, which is publicly available for research has been examined. These databases mostly includes visual, audio, or audio-visual data. [65–69]. The visual modality of the emotional databases includes facial expressions and body gestures. The audio modality includes emotional speech in different languages. These speeches may be acted or natural/spontaneous.

Comparing to audio-visual databases there are fewer publicly available affective, physiological databases. One of them is Healey's recording of 24 drivers (17 of them are publicly available) under different stress conditions [70, 71]. This study includes ECG, GSR and EMG and respiration signals. This challenging database is used for recognition of stress. There are few databases that includes both EEG, peripheral physiological data and facial expressions. Enterface 2005 emotional database is one of the databases include these data which is recorded by Savran et al. [72] Another databases that includes EEG, physiological data and facial expression are DEAP dataset, which is recorded by Koelstra et al. [4] and MAHNOB-HCI that is recorded by Soleymani et al. [2].

4.2 DEAP Dataset

DEAP dataset is a challenging database for emotion recognition that contains Central Nervous System, peripheral physiological response and face video. 32 healthy participants (50 percent females), aged between 19 and 37 (mean age 28.9) participated in the experiment [4]. A participant before the experiment is shown at Figure 4.1.

The experiment starts with a two minute baseline recording, during which a fixation cross was displayed to the participant. Then, the 40 videos were presented in 40 trials.

Figure 4.1: A participant before the experiment, adapted from [4]

Each trial consists the following steps.

1. A 2-second screen displaying the current trial number to inform the participants of their progress.
2. A 5-second baseline recording
3. The 1-minute display of the music video
4. Self-assessment for arousal, valence liking and dominance

The sensors are listed below and placement of sensors is shown at Figure 4.2.

- 32 EEG electrodes that located according to 10-20
- 4 EOG electrodes were located on face. Two of them are located horizontally and two of them are located vertically.
- 2 EMG electrodes were located on zygomaticus major
- 2 EMG electrodes were located on trapezius
- GSR sensor located on finder
- Temperature sensor located on finger.
- Plethysmograph is located on finger.
- A respiration belt also located.

As a last step for a trial participants were asked for self-assessment for four type of feeling. Self Assessment Makins were used for this purpose. SAM contains four different type of feeling. These are arousal, valence, dominance and liking. The

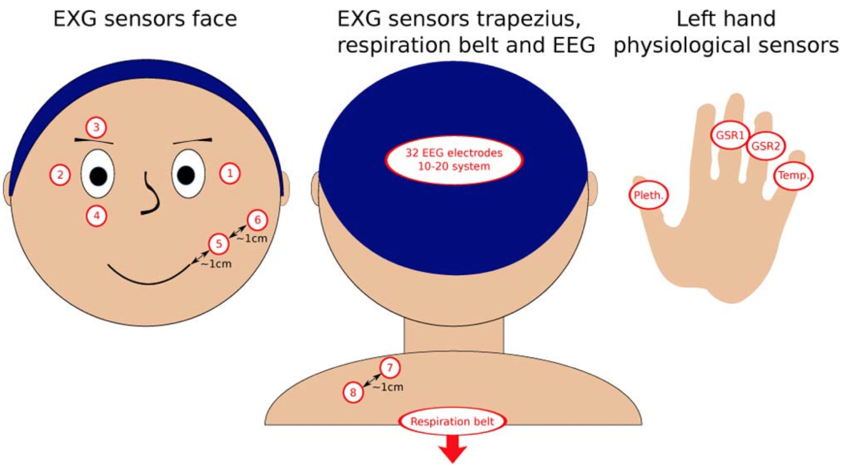

Figure 4.2: Placement of sensors, adapted from [4]

manikins were displayed in the middle of the screen with the numbers 1-9 continuous scale. The valence scale ranges from unhappy/sad to happy/joyful. The arousal scale ranges from calm/bored to stimulated/excited. The dominance scale ranges from submissive/without control to dominant/in control. Fourth scale called liking asks participants personal liking of the video. Finally participants were asked to rate their familarity. (Figure 4.3)

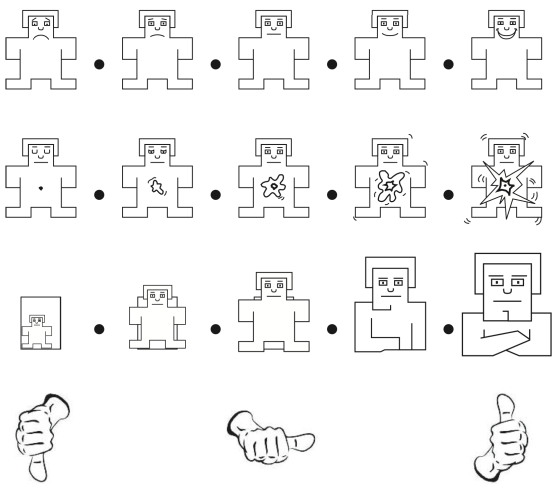

Figure 4.3: Self-assessment Manikins, adapted from [4]

Arousal-Valence (AV) plane divided into four quadrant. These are

LAHV : Low Arousal High Valence

HAHV : High Arousal High Valence

LALV : Low Arousal Low Valence

HALV : High Arousal Low Valence

The mean values and standard deviations of each quadrant is given at Table 4.1 and Table 4.2.

Table 4.1: Mean values of the different ratings for each affect elicitation condition.

Condition	Liking	Valence	Arousal	Dominance	Familarity
LALV	5.7	4.2	4.3	4.5	2.4
HALV	3.6	3.7	5.7	5.0	1.4
LAHV	6.4	6.6	4.7	5.7	2.4
HAHV	6.4	6.6	5.9	6.3	3.1

Table 4.2: Standard Deviations of the different ratings for each affect elicitation condition.

Condition	Liking	Valence	Arousal	Dominance	Familarity
LALV	1.0	0.9	1.1	1.4	0.4
HALV	1.3	1.0	1.5	1.6	0.6
LAHV	0.9	0.8	1.0	1.3	0.4
HAHV	0.9	0.6	0.9	1.0	0.4

EEG and peripheral physiological signals has been recorded using a Biosemi ActiveTwo system on a dedicated recording PC. Stimuli has been presented using a dedicated stimulus PC. Two recording at each dedicated PC has been syncronized using syncronization markers. Signals has been recorded at sample rate of 512 Hz. DEAP dataset has been published in two format. One of them is Original recordings and the other one is pre-processed format.

Pre-processed format of data has been used. This data format includes data items as listed below:

1-32 : EEG

33 : hEOG (horizontal EOG, hEOG1 - hEOG2)

34 : vEOG (vertical EOG, vEOG1 - vEOG2)

35 : zEMG (Zygomaticus Major EMG, zEMG1 - zEMG2)

36 : tEMG (Trapezius EMG, tEMG1 - tEMG2)

37 : Galvanic Skin Response (GSR)

38 : Respiration belt

39 : Plethysmograph

40 : Temperature

Signals have been downsampled to 128 Hz in order to reduce processing time, which is suitable for all kinds of measurements.

In this thesis only peripheral physiological signals were used.

4.3 Feature Extraction

Emotion recognition can be cast as typical pattern recognition task. [73] Emotions are difficulty determined from a single snapshot of the physiological sensors or the brain state. Each modality usually generates sequential measurements spanning the expected duration of the emotion. Contatenation of all data into one single feature vector and apply the classical pattern recognition approaches and methods. [73] In order to generate a model between physiological signals and emotional state, firstly features from preprocessed data has been extracted.

Signals have been used as input, are listed

- Horizontal EOG - hEOG
- Vertical EOG - vEOG
- Zygomaticus Major EMG - zEMG
- Trapezius EMG -tEMG
- Galvanic Skin Response
- Respiration
- Plethysmograph
- Temperature

Basic features of the input signals have been extracted. These features are

- Mean Value
- Maximum Value
- Minimum Value
- Sum of Absolute Value
- Mean of derivative
- Maximum derivative
- Minimum derivative
- Sum of Absolute Value of derivative

- Skewness
- Skewness of derivative
- Kurtosis
- Kurtosis of derivative
- Standard Deviation
- Standard Deviation of derivative
- Entropy
- Entropy of derivative
- Median
- Median of derivative

In total 144 features were extracted from peripheral physiological responses.

4.4 Feature Selection

Feature selection, also named as attribute selection, attribute subset selection or variable selection is the process of discovering most feasible feature set for the construction of the model. Data, which is supposed to be an input for the model, contains many redundant (unnecessary) or irrelevant features. Redundant features are the features which provide no marginal information than the selected features. On the other hand, irrelevant features provide no useful information in any context.

Feature selection methods are a subset of feature extraction field. New features are created from function of the original features at feature extraction phase and then some of these features are eliminated using feature selection techniques. Feature selection techniques are preferred in case of having so many features and few datapoints comparatively. Feature selection process shows which features are important to use and how these features are related, at the data analysis phase.

Feature selection methods provide three main advantages for modeling:

- Improve model interpretability
- Reduce training cost (time)
- Reduce overfitting

Feature Selection is one of the most negotiated topic in pattern recognition field. Complex relationships between emotional states and bodily responses (central nervous system and peripheral nervous system) cause much of the difficulties in emotion recognition area. In some cases, because of the measurement technology and noises, such relationships may be suffered or suppressed.

5. EMOTION MODELING

For the purpose of emotion modeling Fuzzy Cognitive Map has been employed. In this study, the simulations can be collected into two groups. These are

- Regression of Arousal and Valence Value
- Classification of Arousal and Valence Level (Emotional state)

and each of these groups of simulations have been done for two groups of data

- For only one individual (participant)
- For all participants.

It is aimed to examine the accuracy cross the data groups by the change of correlations.

5.1 Construction of Fuzzy Cognitive Map Structure

In a FCM design, the first step is identifying the concepts. For the emotion recognition problem, we want to forecast arousal and valence values of subject. It is clear that we should use arousal and valence concepts as output. As input of the model, we have features of bodily responses of person(s), that we extracted and selected according to their correlation with arousal and valence. 6 concepts are used as input of the FCM model. To represent nonlinearity of the self-tuning strategy some extra inner concepts have been used.

As proposed in [74], it is assumed that input nodes are affecting to the whole other nodes, moreover output nodes are affected by the whole other nodes. The inner nodes are affected from the previous other nodes, and affects to next nodes with a one iteration delay. Therefore, one of the proposed inner concept is affected from the previous concepts representing nonlinearity. In a similar way, is affecting the further inner concepts with a one iteration delay. [74]

Sigmoid function is used as transformation function. λ parameters of the transformation functions have been left free.

BB-BC Optimization Algorithm [59,64] is employed in order to find weight matrix and λ parameters of transformation functions.An illustration of designed Fuzzy Cognitive Map is given at Figure .

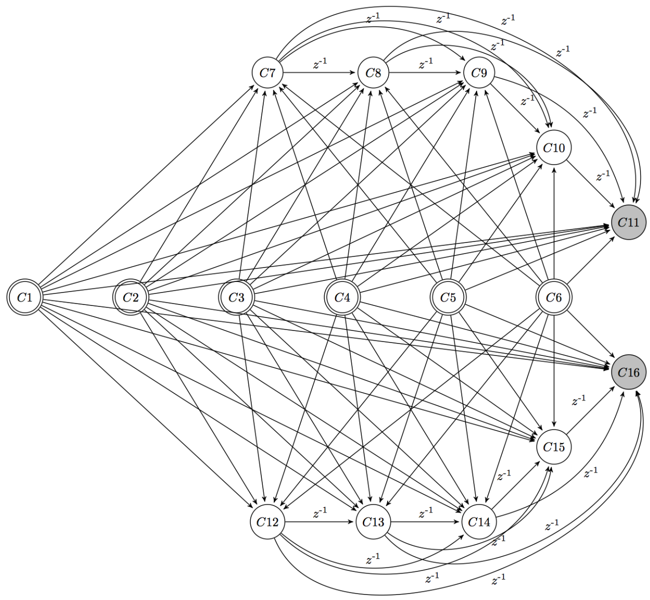

Figure 5.1: Illustration of designed Fuzzy Cognitive Map

In order to optimize parameters of Fuzzy Cognitive Maps, performance criteria is selected as follows;

$$min\left\{\sum_{i=1}^{N} abs(V_{actual}(i) - V_{model}(i)) + abs(A_{actual}(i) - A_{model}(i))\right\} \qquad \textbf{(5.1)}$$

where N indicates the number of datapoints for training, V indicates Valence value, A indicates Arousal value.

5.2 Regression Of Arousal and Valence Values

5.2.1 Participant based regression

For this purpose Participant #7 has been chosen randomly.

5.2.1.1 Feature selection

All features have been extracted for selected participant. In order to select feasible features correlation values of features with arousal and valence values have been examined. Firstly Figure 5.2 shows the correlation values with valence. For the features that have been extracted, most correlated features have a correlation value below 0.6.

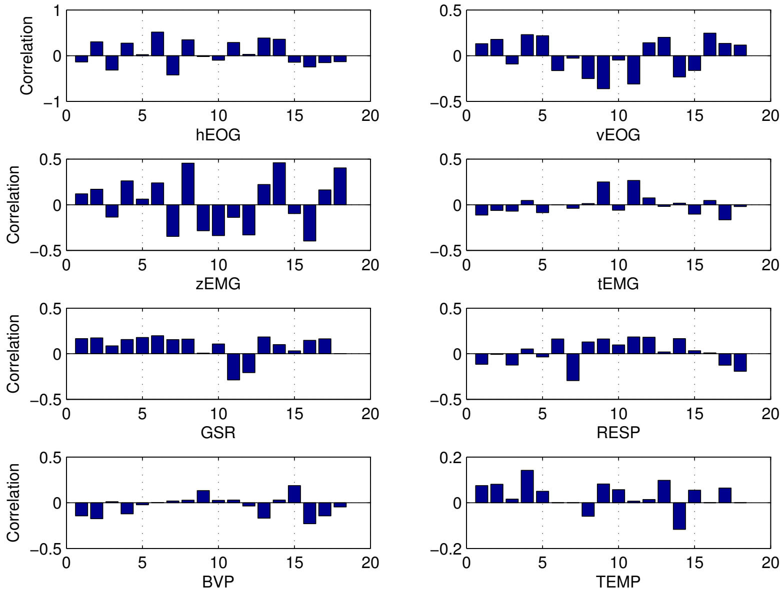

Figure 5.2: Correlation values of extracted features and valence for selected participant

Figure 5.3 shows correlation values with arousal. For the features that have been extracted, most correlated features have a correlation value below 0.5.

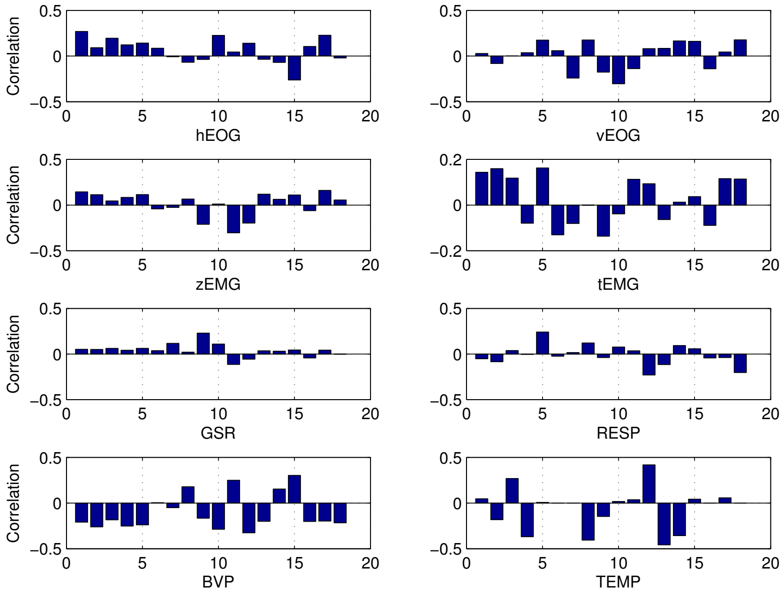

Figure 5.3: Correlation values of extracted features and arousal for selected participant

5.2.1.2 Model

Integral Absolute Error (IAE) is chosen as cost function in determination of the parameters of FCM. Table 5.1 shows the weight matrix of FCM computed by BB-BC Learning Algorithm.

Table 5.1: Computed weight values (Participant Dependent Regression).

$$
W = \begin{vmatrix}
0 & 0 & 0 & 0 & 0 & 0 & -0.49 & -0.63 & 0.38 & -0.88 & 0.79 & -0.94 & -1.00 & -0.88 & 0.16 & -0.36 \\
0 & 0 & 0 & 0 & 0 & 0 & -0 & 0.60 & -0.41 & -0.16 & 0.09 & 0.93 & -0.41 & 1.00 & 0.25 & 0.07 \\
0 & 0 & 0 & 0 & 0 & 0 & 1.00 & -0.49 & 0.71 & 1.00 & 1.00 & 0.50 & -1.00 & 0.70 & -0.53 & -1.00 \\
0 & 0 & 0 & 0 & 0 & 0 & -0.77 & 0.77 & -1.00 & -0.48 & -0.05 & -0.04 & -1.00 & 0.19 & 0.58 & 0.87 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.79 & -0.51 & 0.34 & -0.21 & -0.03 & 0.46 & -0.64 & 0.63 & -0.59 & 0.13 \\
0 & 0 & 0 & 0 & 0 & 0 & -0.44 & 0.74 & 0.32 & 0.17 & 0.66 & -0.61 & -0.38 & 0.10 & 0.96 & 0.91 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & -0 & 0.54 & 1.00 & -0.99 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.21 & 1.00 & -0.61 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.04 & -1.00 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.00 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.23 & 0.33 & 0.40 & -0.62 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.99 & -0.88 & -0.36 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.30 & 0.21 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.57 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{vmatrix}
$$

In addition to weight matrix of FCM, transformation functions of concepts have been optimized by changing λ values of Sigmoid Function.The λ values, which obtained for the concepts are tabulated in Table 5.2.

Table 5.2: λ values for transformation functions (Participant Dependent Regression).

Concept	C_7	C_8	C_9	C_{10}	C_{11}
λ	3.28	2.33	1.52	1.00	2.57
Concept	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
λ	2.35	4.67	1.00	2.07	1.00

5.2.1.3 Results

After obtaining connection matrix and λ values simulations have been run. Figure 5.4 shows the performance of FCM for regression of valence value.

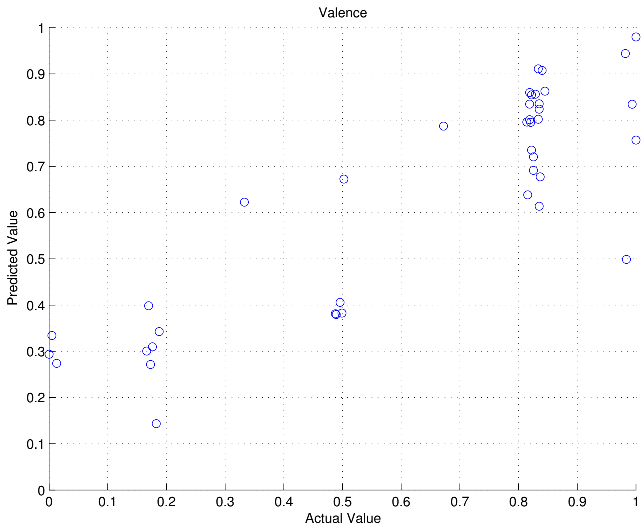

Figure 5.4: Actual and predicted result of valence for selected participant

Figure 5.5 shows the performance of FCM for regression of arousal value.

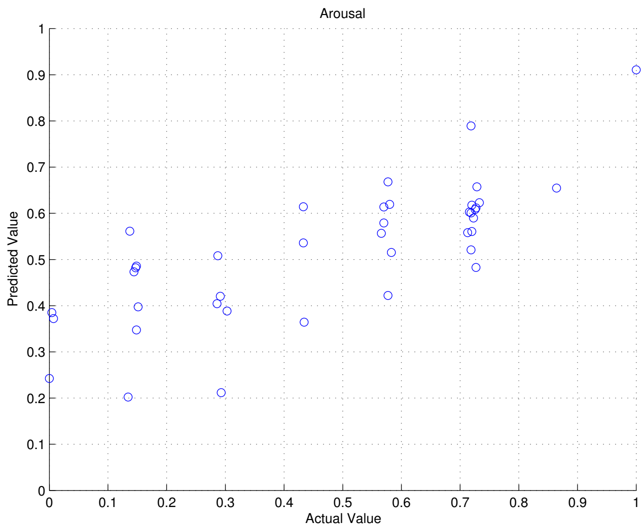

Figure 5.5: Actual and predicted result of arousal for selected participant

5.2.2 Regression based all participants' data

5.2.2.1 Feature selection

All features have been extracted for each participant. In order to select feasible features, correlation values of features with arousal and valence values have been examined. Firstly, Figure 5.6 shows the correlation distributions for each features with valence. Standard deviations of some features are small and these features are more stable to use if they have enough correlation with the valence. For the features that have been extracted, generally mean correlation values are very close to zero that means it is hard to construct a model between output. Moreover, interquartile ranges (IQR) of the features are generally wide, so this decreases the stability of the features. As a third, outliers of some features decreases the stability, and features which have so many outliers is not suitable to use as an input.

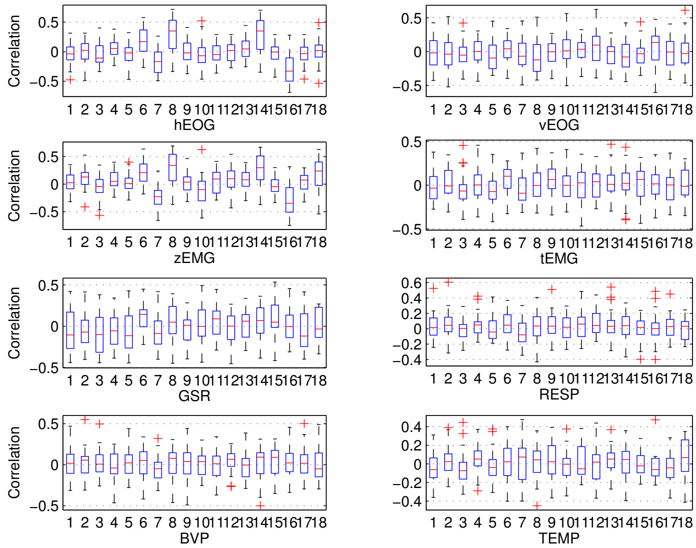

Figure 5.6: Correlation distributions for each features and valence over all participants

Secondly, Figure 5.7 shows the correlation distributions for each features with arousal.

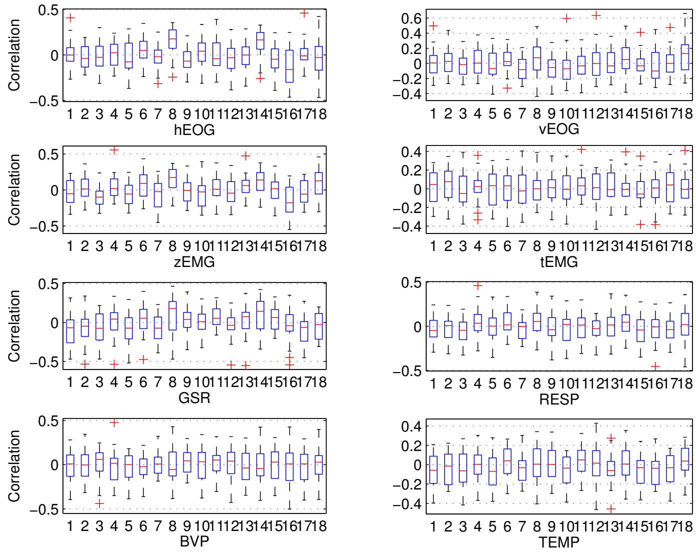

Figure 5.7: Correlation distributions for each features and arousal over all participants

5.2.2.2 Model

Integral Absolute Error (IAE) is chosen as cost function in determination of the parameters of FCM. Table 5.3 shows the weight matrix of FCM computed by BB-BC Learning Algorithm.

Table 5.3: Computed weight values (Participant Independent Regression).

$$W = \left| \begin{array}{cccccccccccccccc}
0 & 0 & 0 & 0 & 0 & 0 & 0.03 & 1.00 & -1.00 & 0.32 & 0.34 & 0.18 & -0.67 & -0.49 & -0.90 & 0.96 \\
0 & 0 & 0 & 0 & 0 & 0 & -0.08 & -0.79 & 0.32 & -1.00 & 0.39 & 0.13 & -1.00 & 0.47 & 0.56 & -1.00 \\
0 & 0 & 0 & 0 & 0 & 0 & -0.24 & -1.00 & -0.17 & 0.60 & -1.00 & -1.00 & 0.48 & 0.21 & -1.00 & -0.62 \\
0 & 0 & 0 & 0 & 0 & 0 & 1.00 & -0.86 & 0.67 & -0.17 & -0.12 & 1.00 & -1.00 & -1.00 & 0.40 & -0.10 \\
0 & 0 & 0 & 0 & 0 & 0 & -1.00 & 1.00 & -0.78 & 0.73 & -0.69 & -1.00 & 0.81 & 1.00 & -1.00 & 0.33 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.66 & 0.56 & -0.73 & -1.00 & 0.20 & -1.00 & 0.28 & 1.00 & -0.85 & 0.61 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & -1.00 & -0.40 & 0.39 & 1.00 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.63 & -0.71 & 0.40 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.00 & 1.00 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.91 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1.00 & -0.03 & -0.97 & 0.16 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.11 & 0.48 & 0.25 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.20 & -0.54 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1.00 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{array} \right|$$

In addition to weight matrix of FCM, transformation functions of concepts have been optimized by changing λ values of Sigmoid Function.The λ values, which obtained for the concepts are tabulated in Table 5.4.

Table 5.4: λ values for transformation functions (Participant Independent Regression).

Concept	C_7	C_8	C_9	C_{10}	C_{11}
λ	1.00	4.47	1.85	1.00	1.00
Concept	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
λ	4.16	1.83	2.94	3.47	1.00

5.2.2.3 Results

After obtaining connection matrix and λ values simulations have been run. Figure 5.8 and Figure 5.9 shows the performance of FCM for regression of valence value.

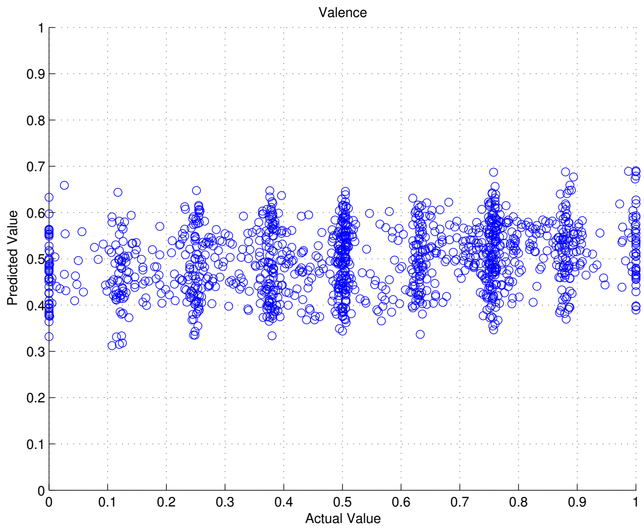

Figure 5.8: Actual and predicted result of valence for all participants

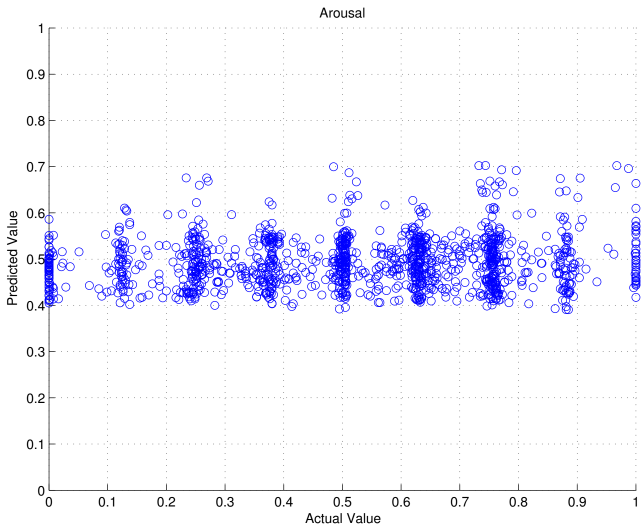

Figure 5.9: Actual and predicted result of arousal for all participants

It cannot be said that, the constructed model performs a good regression. The performance of the regression for both arousal and valence very poor. While analyzing features and their correlations we were aware of the poor performance because of the spread of correlation values for different participants and low correlation values.

5.3 Classification of Arousal and Valence Level

Binary classification is performed on the arousal and valence, which are thresholded into high and low classes.

5.3.1 Participant based classification

5.3.1.1 Feature selection

All features have been extracted for selected participant. In order to select feasible features correlation values of features with arousal and valence values have been examined. Firstly Figure 5.10 shows the correlation values with valence. For the features that have been extracted, most correlated features have a correlation value below 0.6.

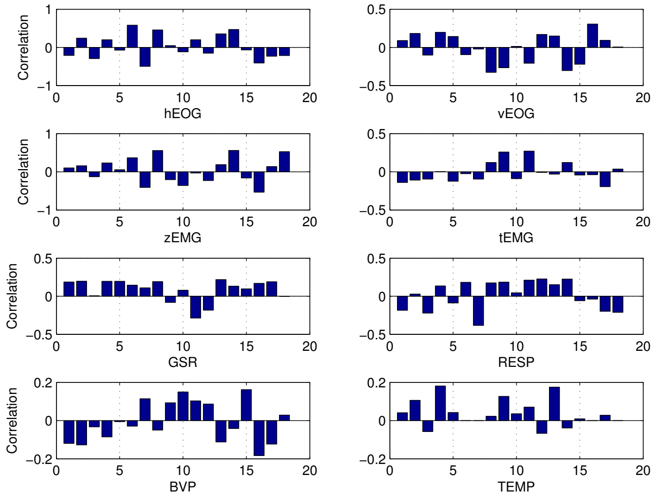

Figure 5.10: Correlations of exracted features and valence level for selected participant

Figure 5.11 shows correlation values with arousal. For the features that have been extracted, most correlated features have a correlation value below 0.4.

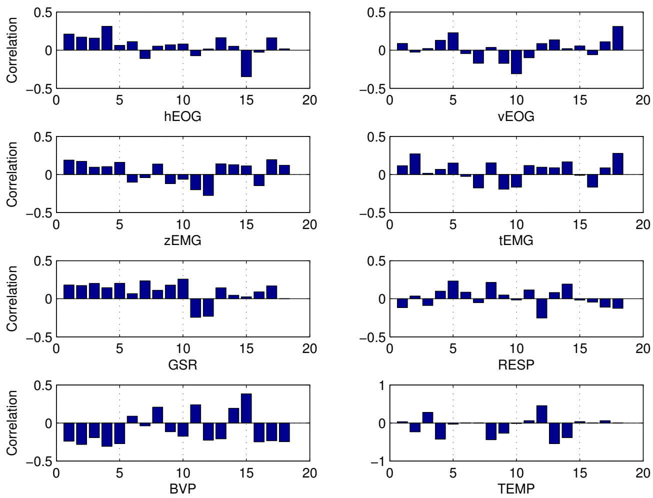

Figure 5.11: Correlations of exracted features and arousal level for selected participant

5.3.1.2 Model

Integral Absolute Error (IAE) is chosen as cost function in determination of the parameters of FCM. Table 5.5 shows the weight matrix of FCM computed by BB-BC Learning Algorithm.

Table 5.5: Computed weight values (Participant Dependent Classification).

$$
W = \begin{vmatrix}
0 & 0 & 0 & 0 & 0 & 0 & -0.63 & -0.79 & -0.71 & 0.74 & 0.94 & -0.35 & 0.12 & 0.42 & 1.00 & -0.19 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.78 & 0.48 & -0.01 & 0.86 & 0.97 & -0.37 & -1.00 & -0.26 & 0.02 & 0.75 \\
0 & 0 & 0 & 0 & 0 & 0 & -0.42 & 0.51 & -0.47 & -0.84 & 1.00 & -0.21 & -0.39 & -0.86 & -0.81 & -0.80 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.11 & 1.00 & -0.36 & -0.77 & 0.47 & 0.88 & -0.22 & 0.42 & -0.49 & -1.00 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.53 & -0.02 & 0.95 & -0.59 & -0.74 & -0.78 & 0.82 & 0.76 & -0.33 & -0.17 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.05 & -0.10 & -0.99 & -1.00 & -0.53 & -0.70 & -0.41 & 0.29 & -0.08 & 0.72 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.50 & 0.40 & -0.29 & 0.43 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.41 & -0.64 & -0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.61 & -0.66 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.19 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.08 & 1.00 & 0.76 & 0.16 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.44 & 0.61 & -0.14 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.80 & 0.31 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.31 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{vmatrix}
$$

In addition to weight matrix of FCM, transformation functions of concepts have been optimized by changing λ values of Sigmoid Function.The λ values, which obtained for the concepts are tabulated in Table 5.6.

Table 5.6: λ values for transformation functions (Participant Dependent Classification).

Concept	C_7	C_8	C_9	C_{10}	C_{11}
λ	1.00	2.88	3.26	3.07	1.00
Concept	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
λ	3.66	2.06	3.31	3.80	1.15

5.3.1.3 Results

After obtaining connection matrix and λ values simulations have been run. Table 5.7 shows the performance of FCM for regression of valence value.

Table 5.7: Classification rates of FCM model for selected participant

Valence (2 class)	Arousal (2 class)	Valence-Arousal (4 class)
90.00%	82.50%	77.50%

5.3.2 Classification based for all participants' data

5.3.2.1 Feature selection

All features have been extracted for each participant. In order to select feasible features, correlation values of features with arousal and valence values have been examined. Firstly, Figure 5.12 shows the correlation distributions for each features with valence. Standard deviations of some features are small and these features are more suitable to use if they have enough correlation with the valence. For the features that have been extracted, generally mean correlation values are very close to zero; that means it is hard to construct a model between output. Moreover, interquartile ranges (IQR) of the features are generally wide, so this decreases the stability of the features. As a third, outliers of some features decreases the stability, and features which have so many outliers is not suitable to use as an input.

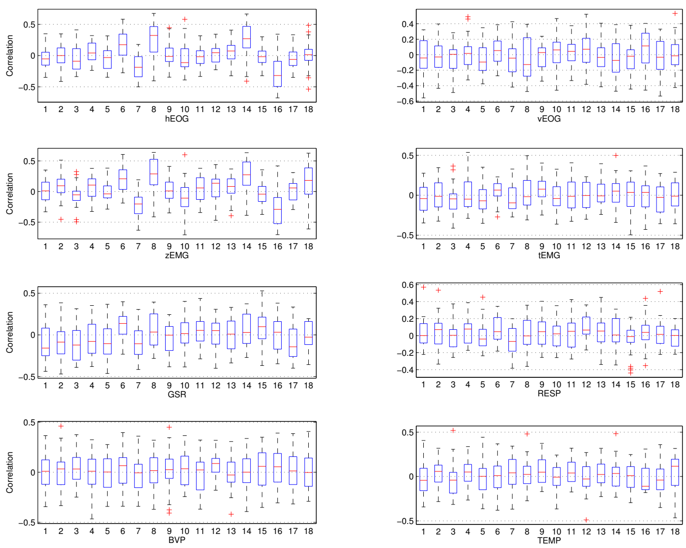

Figure 5.12: Correlation distributions for each features and valence level over all participants

Secondly, Figure 5.13 shows the correlation distributions for each features with arousal.

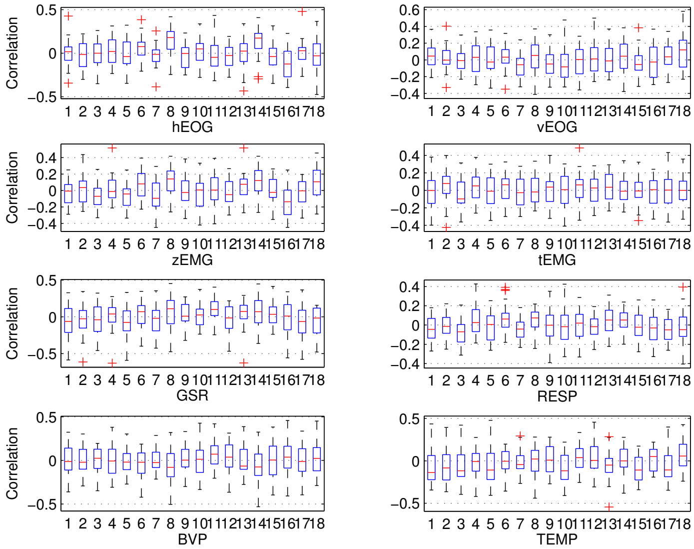

Figure 5.13: Correlation distributions for each features and arousal level over all participants

5.3.2.2 Model

Integral Absolute Error (IAE) is chosen as cost function in determination of the parameters of FCM. Table 5.8 shows the weight matrix of FCM computed by BB-BC Learning Algorithm.

Table 5.8: Computed weight values (Participant Independent Classification).

$$W = \begin{vmatrix}
0 & 0 & 0 & 0 & 0 & 0 & -0.86 & 0.18 & -0.97 & -1.00 & -0.70 & -1.00 & -0.75 & -0.42 & 0.91 & 1.00 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.51 & -1.00 & -0.03 & -1.00 & 0.86 & -1.00 & 1.00 & 1.00 & 1.00 & 0.05 \\
0 & 0 & 0 & 0 & 0 & 0 & -1.00 & -1.00 & 1.00 & -0.40 & 1.00 & -1.00 & 0.55 & 1.00 & 0.04 & 1.00 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.03 & 1.00 & 0.07 & 0.62 & 1.00 & 0.12 & 0.55 & 1.00 & -1.00 & 0.51 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.77 & 1.00 & 0.75 & -0.77 & -0.99 & 0.83 & 0.33 & 1.00 & 1.00 & 0.51 \\
0 & 0 & 0 & 0 & 0 & 0 & -1.00 & 0.74 & 1.00 & -0.27 & 0.50 & -0.93 & -1.00 & -0.77 & 0.26 & -0.96 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.11 & 1.00 & -0.88 & -1.00 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.00 & 0.03 & 0.18 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.48 & 0.80 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.00 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.15 & -0.17 & 0.54 & 0.57 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.43 & 1.00 & 1.00 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1.00 & 1.00 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.67 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{vmatrix}$$

In addition to weight matrix of FCM, transformation functions of concepts have been optimized by changing λ values of Sigmoid Function.The λ values, which obtained for the concepts are tabulated in Table 5.9.

Table 5.9: λ values for transformation functions (Participant Independent Classification).

Concept	C_7	C_8	C_9	C_{10}	C_{11}
λ	1.00	1.00	5.00	5.00	1.00
Concept	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
λ	3.46	3.49	4.87	5.00	4.81

5.3.2.3 Results

After obtaining connection matrix and λ values simulations have been run. Table 5.10 shows the performance of FCM for regression of valence value.

Table 5.10: Classification rates of FCM model for all participants

Valence (2 class)	Arousal (2 class)	Valence-Arousal (4 class)
61.09 %	57.58%	36.64%

It cannot be said that, the constructed model performs a good classification for overall. The accuracy for both arousal and valence very poor. While analyzing features and their correlations we were aware of the poor performance because of the spread of correlation values for different participants and low correlation values.

6. CONCLUSIONS AND RECOMMENDATIONS

This thesis describes the methods by which the emotional processes of humans were modeled and studied using Fuzzy Cognitive Maps (FCM). A public affective database, named DEAP dataset is used. This database includes bodily responses of humans while they are watching music videos.

Firstly, emotional signals have been analyzed in order to use for modeling; physiological signals' characteristics have been examined. After that, features of the continuous signals have been extracted by utilizing basic operators, such as mean, maximum, standard deviation etc. Totally, 144 features have been extracted from physiological signals. It is important to reduce the number of features, that are used for modeling as input; this phase is named feature selection. It is aimed to select most suitable subset of extracted features in feature selection phase. Correlation values of features with the output have been examined and most correlated features have been selected.

In modeling phase, Fuzzy Cognitive Map is utilized for both regression and classification. It is aimed to forecast arousal and valence values in regression part. On the other hand, the purpose of the classification part is to determine arousal and valence class of emotion. These studies have been done for both participant dependent and participant independent cases. Parameters of the fuzzy cognitive map are searched with BB-BC algorithm. Not only weights but also λ values of transformations have been searched.

As a result of the study, it is possible to say that if we improve the correlation rates of the inputs, performance of the constructed model will increase same way. Specialized features for the modalities, such as spectral power density, heart rate, heart rate variability, rise time should be used for modeling instead of using basic features.

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