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AFFECTIVE TECHNIQUES FOR EMOTION RECOGNITION ON MOBILE PLATFORM: A REVIEW

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Abstract

Emotion is a complex state of the mind influenced by events, physiological changes. Recognition of emotion becomes an important subject when it comes to human computer interaction. In the mobile scenario emotion plays an important context in perception and decision making thus given new platform of affective computing often known as Mobile - Human Computer Interaction (Mobile-HCI). Now days, increasing sophistication of devices provides reliable data about human activity and emotion has made possible to develop real time human aware mobile system i.e., mobile technology which is the Ubiquitous Computing. Thus, the current review is all about to provide affective mobile platform for emotion recognition, for the purpose the paper discusses the various methodologies such as tradition method which is based on self reporting and recording user perception for faces and gesture, the second is psycho-physiological method in HCI through which various emotion can be recognized using techniques, like as Electromyography (EMG), Electrodermal activity (EDA), Respiration and Cardiovascular function study for the valence and arousal, while the third method discusses the model for emotion recognition which is the seven fold module for acquisition of emotional data. Finally, the paper discusses about the guidelines i.e., validity, triangulation and, a physiology-driven approach to overcome the constraint like lack of general standard, low accuracy and a doubtful validity of the results.

INTRODUCTION

Emotions play a vital role in people's everyday life. It is a mental state that does not arise through free will and often accompanied by psycho-physiological changes. Recognition of human emotion has a part of affective, cognitive system and increasingly important field of Human Computer Interaction (HCI) because, it does play an essential role in human decision making and memory and physiological satisfaction, sensing and providing user's emotion help application developers to create useful functionalities for users in areas of communication and multimedia thus; becoming an increasingly important field [1]. Research carried out in the field of HCI shows that human have an intrinsic affinity to communicate with computers in a usual and social way i.e., the ability to recognize, understand and express emotion, just like they interact with other people in usual and social situations [2][3][4][5][6].

In mobile scenario too, emotional state acts as an important context in perception and decision making where people rapidly changes places and environments and hence experience rapid changes of emotionally stimulating situation. Simplified emotional computing can aid the developments of emotionally aware mobile companion, mobile monitoring systems, and mobile assistive device. The increasing sophistication of devices provides reliable data about human activity and emotion has made possible to develop real time human aware mobile system [7], which is often known as mobile HCI or mobile technology.

Mobile technology is ubiquitous [8]. Ubiquitous computing applications are exploratory by nature. In the recent year "Ubiquitous information and communication technologies", (ubiquitous ICT's) has now got great economics insignificance. The industrial products are becoming smarter because of their integrated processing capacity, querying remotely, equipped with sensor, etc. Today's mobile phones represents a rich, powerful and ideal computing platform, given their sensing, processing and communication capabilities, that offers an unobtrusive means of obtaining information about the behavior of individuals and their interaction which are the key characteristics. Over 70% of the world populations now have a mobile phone that mainly used as a communication portal to the world. The modern phone have the multitudes of sensors, microphone, cameras, accelerometer, GPS and similar provide the means for application to capture the users context. These communication and sensing capabilities makes the mobile phones an exceptional tool to continuously collect and analyze the activity of users as well as their physiological responses [9].

The current work presents a review for affective techniques for recognition of emotion on mobile platform. Thus paper studies the various measurement techniques, guidelines and, artifact free mobile environments for emotion detection. In the first part of methodology the work discusses about the traditional techniques based on self reporting and recording whereas, the second part suggested the four folded study of psycho-physiological data in HCI. In the first fold, the study undergoes analysis of electromyography (EMG) that measures muscles activity, the second fold measures the electrodermal activity (EDA) that studies the activity of the eccrine sweat glands, while the but one fold measures the respiration and, in the final fold there are sub fold that study the cardiovascular function. In the third part the paper discuss about the model suggested by Syed Shahbaz Hussain, C. Peter and G. Bieber, in which biosensors are used to measures emotion-related physiological parameters of the user.

In the next step, the work discusses about the constraint in capturing the psycho-physiological signal and its related data i.e., the artifacts. Artifacts are a common problem encountered when investigating physiological signals. The physiological signals may be corrupted by power line interference, motion or electrode contact noise [10].Thus the paper also aims to provide an overview of guidelines in mobile emotion measurement (MEM) suggested by J. H. Janssen and E. L. van de Broek, and some techniques to overcome the problems of artifact so as to get effectiveness in recognition of emotion on mobile platform. Finally the paper concludes with the study emphasis on strengths and weaknesses of techniques and methods.

METHODOLOGY STUDY

1. Traditional Method

Traditional Method for emotion recognition based on self reporting and recording a user perception, such as sensual evaluation while self reporting may include questionnaires, narrative techniques and contextual enquires [11]. The observations are based on the observational techniques and video analysis which a very tedious process. Thus, the inter-subjectivity and validity of this approach is hard to guarantee, except this the described techniques approaches to automate expression recognition of facial expression or gesture [12]. The combination of methods gives the broader spectrum of emotion that can be detected [13][14].

2. Psycho-physiological Methods in HCI

The authors [15], suggested the Psycho Physiological method, which offers analysis of certain crucial situations of an experience that are essential for emotional experience, but also provides summative analysis over type [16]. To give more insight into the world of Psycho Physiology, the following section shall give a short overview of method applied for emotional evaluation.

a) Electromyography (EMG)

Access the valance of emotion [17][16][18][19], the techniques measure muscle activity by detecting surface voltage that occur when a muscle is contracted. The positive emotions are recorded only by activation of the *zygomaticus major* muscle, which is activated while laughing, whereas, negative emotions are measured by the *currogators supercilii* muscle, which is activated while frowning.

b) Electro dermal activity (EDA) Measures

The activity of the eccrine sweat glands which is linearly co relate to arousal [20]. Well, tonic EDA is a valid researched and method to arousal and was used for measuring emotions for interaction with system [21, 22].

c) Respiration

Respiration can be used for measurement for negative valence and arousal [23]. Since change in the respiration rate affects the psycho physiological metrics.

d) Cardiovascular function study

The system offers several studies to determine the valence of arousal:

- Blood volume pressure (BVP) - indicates a correlation between greater dilation in the blood vessels with less arousal [24].
- Heart Rate (HR) correlated with arousal.
- Variability of the Heart Rate (HRV) - used as a metric for assessing the positive or negative valence. It is also used as a measure for mental workload.

The methods discuss about providing emotion based personalized services over mobile devices. Since the current work is the restricted to recognition of emotion only.

3. Model Study

The model [25] discusses about providing emotion based personalized services over mobile devices. But, the current work is restricted to recognition of emotion on mobile platform. Thus the model does provide the platform for this purpose using certain components i.e., modules as shown in figure below:

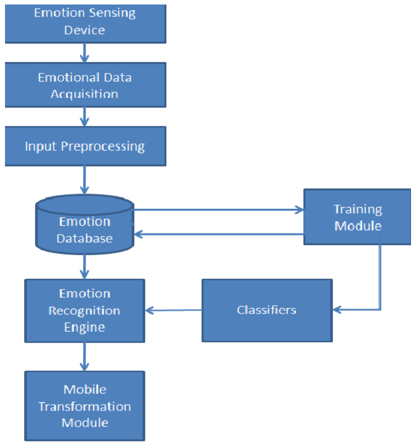

Figure 1 Representation of different modules in the model [27]

The overview of each component is discussed below.

a) Emotional Data Acquisition

The block make use of any biofeedback device for collecting physiological data, or even vision or sound based input devices collecting auxiliary data such as activity data of the person or environmental temperature is beneficial to guage the sensor readings.

b) Input Processing

During the emotion preprocessing phase the collected data is synchronized based on the timestamp which approaches further to the training module and/or to the emotion recognition engine.

c) Processing module

The module consists of the different sensors values along with the auxiliary and user input data, for a particular emotional state. The collected training data is processed by statistical algorithm to form emotion classifiers, which the emotion database for later use in the emotion recognition process.

d) Emotion database

The component stores all data in the table for emotion classifier in the form of templates for emotion pattern matching.

e) Emotion Recognition Engine

The component make use of the statistical approach for analyzing and classifying the emotion for the purpose, the engine uses classifiers generated in the training module to examine input data. Thus, module is known as heart of the model.

f) Classifiers

Multiple classifiers will be created in the training module; each classifier would be classifying the incoming data for particular emotional states.

g) Mobile Transformation Module

This is the output of the model which is the result of measured emotional state of user.

GUIDELINES

The methods discussed above does fall into certain constraint like lack of general standard, low accuracy and a doubtful validity of the results while some related to mobile measurement are discussed below:

- Signal capturing delay between the actual change in emotional state and the recorded change in signal,
- Mobile measurement make physiological sensor sensitive to movement artifact and difference in bodily position,
- Obtrusiveness in some sensor, preventing bridging with the real world application,
- Influence in affective signals due to internal (e.g., a thought) or external factors (e.g., a signal outside) and,
- Time constraint in physiological changes i.e., the change may be for a while or can even be permanent.

To overcome these problems Joris H. Janssen and Egon L. van den Broek [26] suggested some guidelines concerns with mobile emotion measurement (MEM): 1) Validity, 2) Triangulation and, 3) Physiology- driven approach.

1. Validity

There are various methods to trigger emotion but which method trigger participant's true emotion raises the question. The validity plays a crucial issue for MEM. Thus validity is classified into four types: content, criteria related, construct, and ecological.

Content validity means the agreement of experts on the domain of interest or, the degree of features represents a construct, or the degree of set of features of a given sets of signals that represent all facets of domain. Criteria-related validity handles the quality of the translation; emotion preferably measured at the moment they occur, as is feasible with MEM. However, measurements before (predictive) or after (postdictive) the particular events are more feasible. A construct validation process aims to develop a nomological, or ontology or sementic network, build around the construct of interest but to build such a network requires theoretical grounded, observable, operational definitions of all construct. Such a network aims to provide a verifiable theoretical framework. And finally the ecological validation refers to the influence of the context on measurements. Since, emotions are easily contaminated by contextual factors, using a similar context as the intended application for initial learning of vital importance. Hence emotion measurements done in controlled laboratory settings, are poorly generalize to real world application.

2. Triangulation

Heath [27] defines triangulation as "the strategy of using multiple operationalizations of constructs to help separate the construct under consideration from irrelevancies in the operationalization". Thus this principle of triangulation can be applied to the human computer interaction and if thus to mobile HCI too, that can deal with the noisy physiological signals inherent to MEM.

3. A physiology-driven approach

The final guideline stems from the idea that physiological emotion measurement can never be entirely based on physiological changes, there are many factors outside one's affective state that contaminate affective signals.

The table with respect to source below illustrates the summary; infer the mental state from physiological signals.

Table 1: A summary of 11 studies that have tried to infer a mental state from physiological signals. They all employed a similar approach: first, a certain mental state (e.g., stress, certain emotions, mental workload) is induced in participants, while a number of physiological signals are measured. Subsequently, a variety of features is extracted and pattern recognition and machine learning techniques are employed to enable the automatic classification of the emotional states [C].

Source	Signals	Features	Selection/Reduction	Classifiers	Target	Result
[28]	*C,E,R,M*	40	SFS, Fisher	LDA	8 emotions	81 %
[29]	*C,E,S*	3		kNN LDA	6 emotions	69 %
[30]	*C,E,B*	18		SVM	6 emotions	42 %
[31]	*C,E,S*	10		SVM	3 emotions	78 %
[32]	*C,E,S*	12		kNN, LDA, ANN	6 emotions	84 %
[33]	*G*	3	PCA	ANN	4 emotions	90 %
[34]	*C,G,R,M*	22	Fisher	LDA	3 stress	97 %

					levels	
[35]	*C,G,S,M,P*	46		kNN, SVM, RT, BN	3 emotions	85 %
[36]	*C,G,S,P*	11		SVM	2 stress levels	90 %
[37]	*C,E*	20	ANOVA	SVM, ANN	2 fun levels	70 %
[38]	*C,E,M,R*	15		SVM, ANFIS	4 affect states	79 %
[39]	*E,M*	10	ANOVA, PCA	kNN, SVM, ANN	4 emotions	61 %

Notes: *C*: Cardiovascular activity; *E*: Electrodermal Activity; *R*: Respiration; *M*: Electromyogram; *B*: Electroencephalo- gram; *S*: Skin temperature; *P*: Pupil Diameter; ANN: Artificial Neural Network; RT: Regression Tree; BN: Bayesian Network; SVM: Support Vector Machine; LDA: Linear Discriminant Analysis; kNN: k Nearest Neighbors; ANFIS: Adap tive neuro-fuzzy inference system; PCA: Principal Component Analysis; SFS: Sequential Forward Selection.

CONCLUSION

The paper described some methods for emotion recognition. Every method has its strength and weakness, also strongly depending on the evaluation context. Firstly the traditional method which support in recognition of emotion with respect to face and gesture on the desktop platform. But, how this method support accessing emotions in a mobile context remains unsolved.

Secondly, about the psycho-physiological methods in HCI, this is based on firsthand experience. The method is carried with respect to motion aspect in mobile situation and research based on movement and psycho-physiological measurement methods. In which, EMG provides more accurate result than facial expression recognition with video analysis because low evocative emotions are difficult to recognize visually, though it is a viable and reliable method to measure positive and negative emotional states even when participant is moving. Viz., sensors with cable are attached in the face, which is obtrusive for participants. In case of EDA, is a well researched and valid method to record arousal but , the main constraints of EDA are the room temperature, humidity, participant activities and the correct attachment of the electrodes. Further, respiration also plays an important role in measurement of negative valence and arousal. The method also suggested the study of cardiovascular function related to 'HR', 'HR', 'BVP' to determine the valence and arousal, this method should not be applied unimodal because, a multimodal approach is more accurate and results in a broader spectrum of emotion but has the disadvantages that multiple channels have to be combined, analyzed and finally interpret.

In the third model method, also suggest the useful technique for recognition of emotion. It consists of set of modules, but the acquisition of emotional data is captured through emotion sensing device thus, the physiological data may comprise of artifact that encounters the problem in investigating the emotion. These artifacts are more problematic in mobile setting. To overcome the constraints, MEM guidelines overcome the problems and fit the ambient intelligence vision perfectly. Although combining wearable and intelligent devices into smart environments is a great challenge but, holds a great promise for future technology and lifestyle.

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