Using Physiological Signals for Emotion Recognition

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Abstract. **Recognizing user's emotions is the promising area of research in a field of human-computer interaction. It is possible to recognize emotions using facial expression, audio signals, body poses, gestures etc. but physiological signals are very useful in this field because they are spontaneous and not controllable. In this paper a problem of using physiological signals for emotion recognition is presented. The kinds of physiological signals and sensors are described. The models of emotions, the methods of emotions' elicitation are presented. There is also a brief review of research progress in using physiological signals for emotion recognition presented in literature. It leads to conclusions about challenges and possible future research.**

***Keywords*: emotion recognition, physiological signals, affective computing.**

I. Introduction

COMPUTERS do not have emotions but if we would like the human-computer interaction to be the most natural ones computer should take into account humans emotions. Affective computing is relatively young field of computer research, emotions have been considered by computer researchers for about last twenty years [1].

People show their emotions by facial expressing, tone of voice, posture, gestures but also through the physiological signals. Emotion recognition using electrophysiological signals is one of the branches of the affective computing and many researchers use biosignals to estimate people affect. Physiological signals are very useful because, in the opposites to other signals, they are not controllable by people - suppressing or masking biosignals representing affects is impossible - and they are strongly correlated to human emotions.

People often express their emotions during interaction with computer but computer do not recognize it. It is not necessary that computer always pay attention to humans emotions but it can be very useful in many field: health care [2], games, e-learning, etc. The applications taking into account human emotions would be more comfortable for users, very useful for medical applications especially to aged people [2], for car drivers [3]. Also polygraph works exploit changes in emotions and examine physiological signals like blood pressure, pulse, respiration, and skin conductivity. Physiological signals can be useful for patients with autism etc., who will not be able to express their emotions explicitly [4]. So there are many possible applications of emotion recognition using physiological signals.

This paper gives a short review of physiological signals and sensors, emotions and summarizes selected work of different researchers in the field of using biosignals in emotion recognition. The paper is organized as follows: section II describes kinds of physiological signals and sensors used for recording them. Section III describes the emotions: models and the ways of emotions' elicitation. Section IV presents a short review of previous research in emotion recognition using physiological signals. Section V include conclusions and future work.

II. Physiological Signals

Human being is a very complicated individuality. There are many physiological signals that can be collected to give us information about human health, emotions, etc. Bellow are shortly described those that are useful for emotion recognition [5], [6].

A. Kinds of physiological signals

Cardiac function. The heart is a muscular organ located in the left side of the chest. Analysis of its work gives us many information about people's health. A heartbeat is a series of electrical impulses, involving depolarization and repolarization of the muscle. The electrical waveforms can be recorded using electrodes placing on the chest. With every heart beat, the volume of blood is pushed through the body's blood vessels. Generated pulse wave travels from the heart to all regions of the body.

Temperature is very simple but useful physiological signal. It depends on the measurement's place in the body, the time of day, activity of the person. The temperature changes can reflect variations in mood and emotions.

Muscle electrical activity occurs during muscle contraction and relaxation cycles. Facial electromyogram can be very useful for emotion recognition but the electrodes fixed on face are too uncomfortable and intrusive for a user and then useless in practice.

Respiration allows people for gas exchange. During breathing the chest and the diaphragm in sequence push up and fall down. The depth and speed of the respiration can reflect the state of health, people's condition and affects.

Skin conductance is a signal that measures the electrical conductance of the skin. This signal changes if the skin is sweaty. It is related to stress situations and another affects. Skin conductance is used as an indicator of arousal. This

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signal is used e.g. in polygraph.

Electrical activity of the brain is very useful signal that can provide valuable information about human behavior.

B. Sensors

Recording physiological signals requires connection people with biosensors. All the sensors are not invasive but sometimes can be intrusive and uncomfortable for users. The special equipment, necessary to collect and analyze the physiological signals, is not easy available for computer users like e.g. mouse or web camera, though measurements of physiological signals are rather performed in laboratory then in real life. The disadvantage is that using electrodes is sensitive to motion of users body [7] what matters when we try to recognize emotions. However it seems to be only a matter of time the sensors will be available in real-life equipment, e.g. Sony plan to provide a Playstation controller with temperature or heart rate sensors.

There are various devices for physiological data collection. Many researchers often use following two: World-renowned PowerLab Data Aqusition System with Chart software [8], [9] and ProComp Infiniti from Thought Technologies [10], [5], [11]. The devices use many different sensors for measuring selected physiological signals. Some sensors used in emotion recognition are shortly described below [5], [6].

Blood volume pulse (BVP, also called photoplethysmography) sensor detects blood flow by using infrared light through the tip of a finger and measuring how much light is reflected.

Electrocardiography (ECG) device detects the electrical changes on the skin that are caused by depolarization of the heart muscle during each heartbeat. The typical ECG wave is presented in the Fig. 1a [7].

Both BVP and ECG sensors detect a specific physiological change associated with the heart's activity, but their functions are based on different principles.

Temperature (T) sensor detects the body temperature. It is easy to measure this signal and also the changes in time caused e.g. variations in peoples excitement. The most commonly used a skin temperature (SKT) sensor describes the temperature as measured on the surface of the skin. The sensor is usually fixed on fingers.

Electromyography (EMG) sensor allows to measure micro electric impulses generated by muscles during their activity. The amplitude of an electric signal is proportional to the power of the muscular contraction. Muscle activity typically shows only strong emotions because changes of EMG values can be too small to estimate valence [10].

Skin Conductance (SC) sensor measures the electrical conductance of the skin and is often placed on finger. Sometimes the sensor of Galvanic Skin Resistance (GSR) is used.

Respiration (RSP) sensors measure how deep and fast a person is breathing. It is also correlated with people's emotions.

Electroencephalography (EEG) sensors are electrodes placed on the scalp. They can record the electrical activity of the brain. It is a valuable tool for research and diagnosis.

Some examples of the physiological signals and the sensors' position on body are presented in the Fig.1 [7].

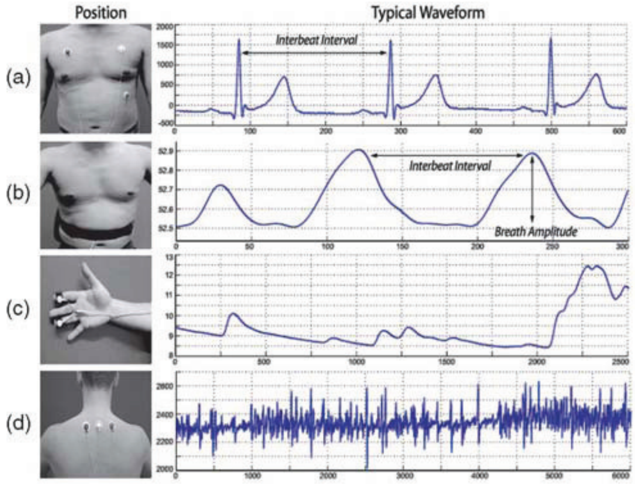


Fig. 1. Biosensors position and typical waveforms (a) ECG (b) RSP (c) SC (d) EMG. [7]

III. Emotions

Emotions accompany people all their live. Generally, emotion is a mental state or feeling that arises rather spontaneously and is often accompanied by physiological changes [12]. Contrary to mood, which can last for hours or days, emotions last only few seconds or minutes.

A. Models of emotions

It is not a trivial problem to create a model of emotion. In a literature there are various theories of emotions and several affect models developed for different application fields [13]. One approach is to divide the emotions into a discrete categories that can be described by a set of word labels like joy, happiness, sad etc. Unfortunately not all emotions can be expressed in this way because some of them are mixed and it is not easy to classify them to proper category.

American psychologist Ekman was one of the first researcher that systematically take up the problem of human emotions and he proposed the discrete emotional model using six universal emotions: *happiness*, *surprise*, *anger*, *disgust*, *sadness* and *fear* [13].

The second approach is to categorize emotions into multiple dimensions space with continuous scales [7]. So the person can indicate his impression about elicited emotion on these scales (Fig.2a).

Lang has investigated that emotions can be expressed in two dimensional space by *valence* and *arousal*. In his model valence reflects pleasant or unpleasant in affects (positive/negative) and arousal reflects changes from calm to excited [14].

The next popular model of emotions is PAD which describes the human emotional state with three dimensions: *pleasure*, *arousal*, and *dominance* [15]. Pleasure signifies negative-positive valence of emotion and changes from unpleasant to pleasant. Arousal expresses intensity of emotion and ranges from inactive (e.g. bored) to active (e.g. excited). Dominance defines whether an emotion is dominant or submissive.

In Plutchik's model there are eight fundamental emotions: *joy*, *trust*, *fear*, *surprise*, *sadness*, *disgust*, *anger* and *anticipation* [16]. He presented these basic affects and also other advanced, composed of the basics, on the color wheel of emotions (Fig.2b).

In the Fig.2c there is the 2D model of emotions with visualization of Plutchik's eight primary emotions [2].

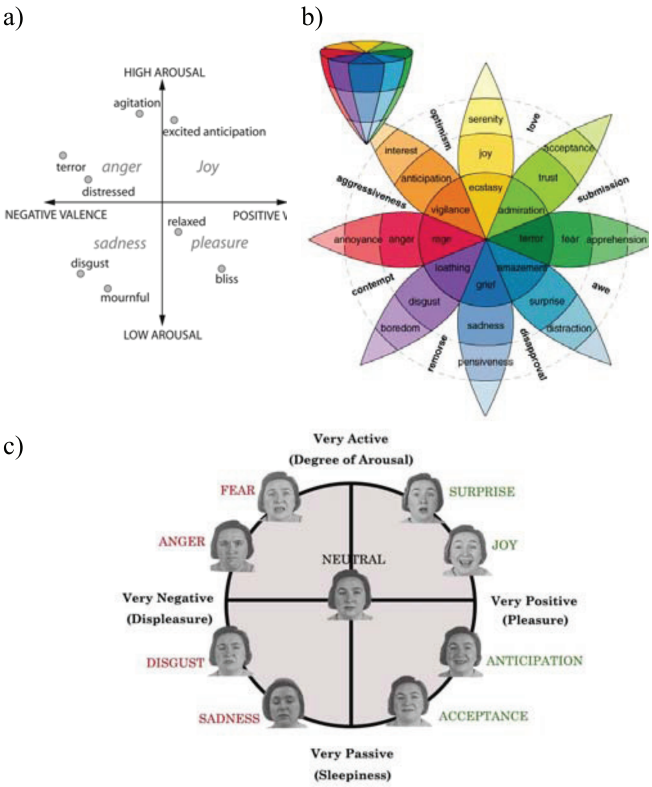


Fig. 2. Emotion models (a) Two-dimensional model by valence and arousal. [7], (b) Plutchik's color wheel of emotions [17], (c) 2D model of emotions with visualization of Plutchik's eight primary emotions [2].

B. Emotion elicitation

It is possible to imitate emotions when we use facial expression for emotion recognition. The user can be asked to feel or express some of them. The results sometimes are quite good but sometimes they are far from the real emotions. When we want to evaluate the physiological signals the emotions must be real.

There are many methods for emotions elicitation. The most popular use images, sounds, music, films and games. Using such stimuli gives, as a result, the authentic, truthful emotions.

Gross and Levenson investigate many film clips to discover 16 movie clips that are the best to induce eight different emotions: *amusement*, *anger*, *contentment*, *disgust*, *fear*, *neutrality*, *sadness* and *surprise* [18]. These films were successfully used by researchers to elicit this emotions ([19]). It is not a trivial problem to choose stimuli that always, for all the people elicit the same emotion. In [8] researchers examine several film clips to induce 13 different emotions, but they investigate that only for three emotions: fear, joy and neutral there were chosen successfully. They evaluate only these three emotions with physiological signals.

The International Affective Picture System (IAPS) with the International Affective Digitized Sound System (IADS) are a collection of stimuli that are available to researchers in the study of emotion and attention [20], [21]. The affective norms (ratings of pleasure, arousal, and dominance) for the pictures in the IAPS were obtained in 18 separate studies involving approximately 60 pictures each [20]. However, some researchers observe that emotions elicit by images can be different from the expected ones [13].

IV. PHYSIOLOGICAL SIGNALS IN EMOTION RECOGNITION

The psychophysiology gives an assumption that there is a relation between physiological signals and arousal/valence because activation of the autonomic nervous system changes while emotions are elicited [10]. It is possible to recognize emotions using facial expression, audio signals, body pose, gestures etc. but physiological signals are very useful in this field. People are sometimes able to control their facial expression, voice but it is impossible or extremely difficult to control natural reactions of our body like changes of temperature or heart rate [2]. Then the physiological signals do not depend on human will and can be objective source of information about human emotions.

Emotion recognition is interesting, giving a potentially large possibilities, but very difficult task. Some researchers limit the recognized emotions to only a few ones [22], [23], [7]. There is a problem to find a baseline that the signals will be compared with. The most common solution is to use a rest period when the user not reveal any emotions. Then the physiological changes through the emotions can be compared with these parameters from that baseline [5].

It is also a problem to find the best emotion-relevant features and to correlate them with emotional states. In literature often are used: *mean*, *standard deviation*, *first derivative*, *high frequency* and *low frequency powers*, *Fourier* and *Wavelet Transform coefficients* etc. [24].

Researchers create their own databases in order to recognize emotions, test different algorithms. One of the existing database - DEAP - contains 32 participants and considers signals from following sensors: EEG, EMG, face EMG, BVP, SC, T, RSP [25].

A. Literature review

In table 1 there is a short review of previous research in emotion recognition field using physiological signals. In the table is shown which physiological signals were analyzed by researchers, which emotions were recognized, what stimuli was used and which methods of classification were adapted. Also efficiency of recognition is shown.

In the literature can also be found papers describing only a conception of research: planned experiments, stimuli, considering biosignals etc. In [26] authors plan to use the MIT Media Lab sensors to record EEG, eye activity, facial expression, their own database of images as a stimuli and recognize three emotions: happy, sad and surprise. Also in [10] a concept of researches is presented. As a stimuli was planed a card game called "Skip-Bo", the device -

ProComp Infiniti. Using EMG and skin conductance with Bayesian Network as a method of classification they plane recognize fear, frustration, relaxed, joyful and excited.

TABLE 1: A SHORT REVIEW OF PREVIOUS RESEARCH IN EMOTION RECOGNITION USING PHYSIOLOGICAL SIGNALS.

Participants	*Physiological signal*	*Devices*	*Recognized Emotions*	*Stimuli*	*Methods of classification*	*Efficiency (recognition rate) %*	*Literature*
			pleasure/ displeasure			60	[22] 2004
12 (male, native Japans)	EEG SC BVP		joy, anger sadness, fear relax	Audio-visual	SVM	16,7 (sadness) – 58,2 (joy)	
31 students	T, HR, GSR	BodyMedia SenseWear Armband	sadness, fear, anger, surprise, frustration, amusement	movie clips	k-Nearest Neighbor (KNN), Discriminant Function Analysis (DFA)	50-90	[19] 2003 [27] 2004
4 (3 males, 1 female)	EEG BVP blood pressure HR, RSP, T	Biosemi Active Two device (EEG)	arousal of emotions	IAPS	naïve Bayes, Fisher Discriminant Analysis (FDA)	50-72	[13] 2006
5 (3 sessions, each session 30 trials)	EEG, GSR, RSP, T, BVP		calm, positively excited, negatively excited	IAPS	k-Nearest Neighborhood (KNN), Linear Discriminant Analysis (LDA)	50-70	[6] 2008
3 males	EMG, SC, ECG, RSP	ProComp Infiniti	four musical emotions: joy, sad, irritating, pleasure	musical induction method (4 songs, 1 for each emotion)	Extended Linear Discriminant Analysis (pLDA), EMDC	65-95	[7] 2008
1 person (25 days)	EMG, SC, ECG, RSP		joy anger sadness pleasure	dataset from Multimedia and Signal Processing Lab, Augsburg University, Germany [29]	Adaptive Hierarchical Genetic Algorithm (AHGA), improved evolution strategies (IES) based on Cauchy Distribution	50-85	[28] 2009
2 sets of 87 data for training and 2 sets of 87 data for testing	ECG	Wireless Bio Sensor RF-ECG	fear anger disgust sadness joy neutral	IAPS	The Least Significant Difference (LSD) test	61,79	[2] 2010
12 college students (6 males, 6 females)	Electrodermal activity (EDA) ECG, SKT, BVP		negative emotions: sadness fear surprise stress	10 emotional stimuli sets, audio-visual film clips	Linear Discriminant Analysis (LDA), Classification And Regression Tree (CART), Self Organizing Map of Neural Network, Naïve Bayes, SVM	51-100	[23] 2012

B. *Research concept*

Literature analysis has shown that there are many unresolved problems. So we plan a series of experiments that allow to recognize different kind of emotions using multimodal data: physiological signals for implicit tagging and facial expression and audio signals for explicit tagging of emotions [30]. Although, in the research the electroencephalogram (EEG) and facial electromyograms occurred useful for emotion recognition but on account of electrodes on the scalp or face these sensors seems not to be tolerable for practical use in real life [25]. Then from the set of physiological signals we consider skin conductance, blood volume pulse, heart rate, respiration, temperature and muscle electrical activity.

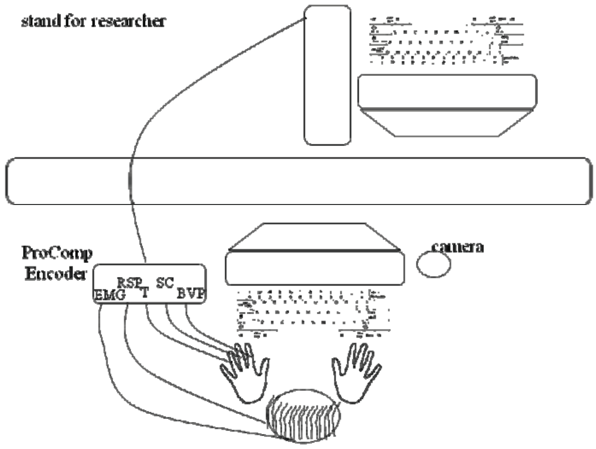
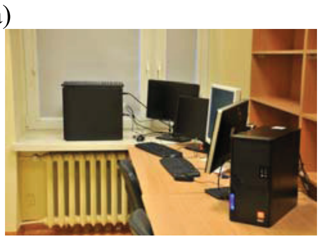


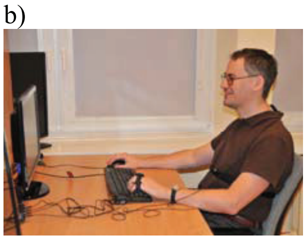
Fig. 3. Experiment scene for acquisition physiological signals for emotion recognition.

In Fig.3 an experiment scene for study emotions is presented. Some initial tests were performed and they indicate the correlation between physiological signals and emotions. The device used for experiment is ProComp Infiniti from Thought Technologies [5]. In Fig.4 there is a real experiment scene for testing emotions.

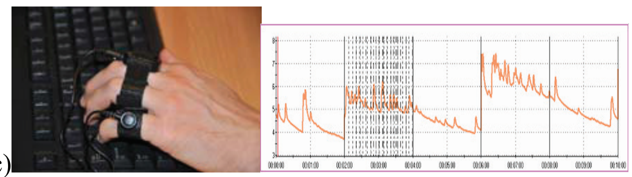
a)



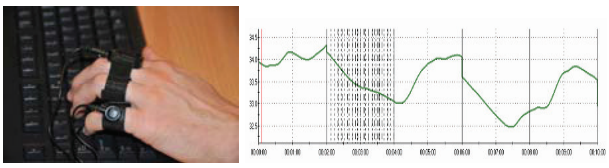
b)



c)



d)



e)

f)

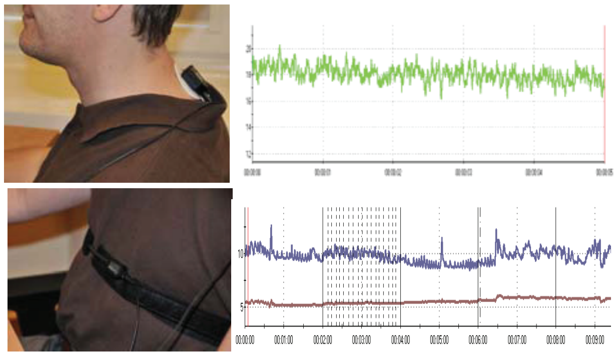


Fig. 4. Experiment scene for testing emotions using physiological signals and video image (a) stand for researcher (b) stand for subject. Biosensors' position and sample of waveforms (c) SC (d) T (e) EMG (f) RSP.

V. CONCLUSIONS

In this paper a short review of using physiological signals for emotions recognition was presented. More and more researchers see about affect recognition. Using physiological signals in this field has many advantages: they are spontaneous, no controllable, culture and education independent and strongly correlated with people emotional state. Biosignals' sensors are not good in real life but very suitable for verification in laboratory due to their intrusiveness. The review of literature shows that some problems have been resolved but many of them still wait for a resolution. Currently there is no system for recognition all humans emotions. The efficiency of recognition also can be improved.

Thus in our future work we would like to take advantage of emotion recognition in affect aware games, e-learning and software engineering [31]. The emotional state of user will be feedback to applications and will allow to influence on them. People are able to recognize emotion basing on holistic image of human: facial expression, tone of voice, words spoken, gestures etc. and we would like to use not only biosignals but also facial expression, standard input devices [32] and audio signal.

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