Bio-sensing for Emotional Characterization without Word Labels

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Abstract. In this article, we address some of the issues concerning emotion recognition from processing physiological signals captured by bio-sensors. We discuss some of our preliminary results, and propose future directions for emotion recognition based on our lessons learned.

Keywords: Emotion Recognition, Affective Computing, Bio-sensing.

1 Introduction

In the past few years, a number of psychologists [1-3] have challenged the classical notion that emotion can be categorized by labels, using words such as 'anger', 'fear', 'happiness' [4], and have proposed to use dimensional representations of emotions for more realistic categorization of emotional states. Emotion labeling has also been found to be dangerously ethnocentric and misleading [5].

Our current reported work is one of the first attempts to approach automatic emotion recognition with the novel method proposed by Peter and Herbon [6] that moves away from the notion of labeling emotional states with discrete categorical words. In the following section we describe which physiological modalities associated with emotions we chose to capture, the bio-sensors that we used, and the emotion elicitation method used with participants. The section after that explains how we created a data set suitable for training and testing emotion classifiers, and the processing of these bio-physiological signals for classification. Finally we discuss some of the lessons learnt from this experiment and propose future directions toward emotion recognition.

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2 Emotion Recognition without Labeling Emotion with Words

Peter and Herbon [6] have proposed a method for avoiding the use of words for automatic emotion recognition and provided guidelines about how to structure emotions as a dimensional representation for the use in human-machine interaction. Labeling emotions can be problematic because the category borders are blurry and the word 'anger' for instance can describe many different emotional states. The method as described by [6] avoids these problems because it abandons labeling emotions with words.

The procedure to classify emotions for automatic emotion recognition proposed in [6] consists of the following four steps:

- Step 1: Elicit emotions while measuring physiological signals and ask test subjects to self-report in a way that can be translated into a dimensional structure.
- Step 2: Assign the physiological measurements to the related ratings.
- Step 3: Group emotions into clusters with similar physiology and place in dimensional structure.
- Step 4: Identify characteristic patterns in physiology for each cluster.

In this section we describe which sensor modalities we chose to capture and process the physiological signals that are associated with emotional states. We describe the emotion elicitation method based on psychological findings designed to collect data while eliciting emotions from the participants. With these experiments we completed step one and two of the procedure described by [6].

2.1 Bio-sensors Used to Collect Data

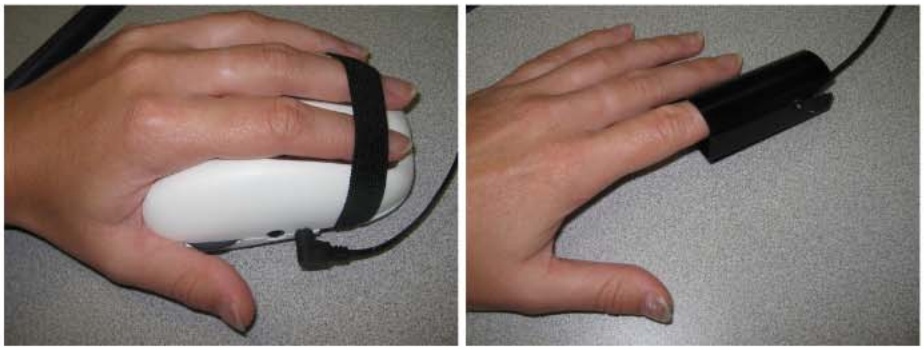
Our data set consisted of multimodal physiological evidence about the affective state of a user: galvanic skin response (GSR), and blood volume pressure (BVP). For a survey of the different modalities associated with emotional states and the recognition methods used to process these various modalities to date see [7].

Galvanic Skin Response (GSR): The GSR2 Thought Tech LTD device[1] shown in Figure 1.a was used to measure the Galvanic Skin Response (GSR). This method was introduced in the early 20th century and is based on the idea that conductance of an electric current is easier on moist skin. The autonomic nervous system, which consists of two subsystems – the parasympathetic and the sympathetic subsystems – has an influence on the control of sweat glands. In the case of higher sympathetic activity, the sweat glands get more hydrated and skin conductance increases. So, the sweat glands are used as resistors and the skin conductance can be measured with the GSR device by passing a small electric current across two electrodes that touch the skin.

Blood Volume Pressure (BVP): The Pulse Plethysmograph[2] shown in Figure 1.b. was used for measuring the Blood Volume Pulse (BVP), a signal from which information about the Heart Rate Variability (HRV) can be computed. HRV has been

[1] http://www.thoughttechnology.com/gsr.htm
[2] http://www.ufiservingscience.com/Pig1.html

linked to emotional processes and the autonomic nervous system [8]. In addition, information about vasoconstriction (constriction of the blood vessels) can be inferred by detecting a decrease in the amplitude of the BVP signal. Vasoconstriction is said to be related to emotional processing as well [9]. The sensing device shown in Figure 1.b. is a finger clip that uses an infrared emitter and receiver to measure the amount of light that is reflected back by the skin.



(a) (b)

Fig. 1. (a).The GSR2 skin conductance device (Thought Tech LTD) (b). Pulse Plethysmograph.

2.2 Emotion Elicitation

We created an experimental set-up with the sensors described above in which test subjects were exposed to emotion eliciting stimuli, and data was captured from the sensing devices during that exposure. During the experiment, the physiological signals were measured with the non-invasive sensors while the participant was asked to keep the arm that was attached to the sensors as motionless as possible (to avoid generating noise data associated with body movements).

Stimulus design: The stimuli used for emotion elicitation consisted of movie fragments that were known to elicit a range of different emotions. Gross and Levenson [10] conducted a very thorough study to provide a selection of movie fragments best suited to elicit certain emotions. Using a large amount of test subjects and a wide selection of movie fragments they were eventually able to reduce it to a reliable set in terms of emotion discreteness and intensity. More recently, Nasoz et al. [11] performed another panel study in which they tested the movie selection again, and created a modified version of the movie selection which proved more appropriate. In order to allow for easy comparison of previous emotion recognition classification, our set of emotion eliciting movie clips was based on the selection of [11]. Some changes have been made though because during a pre-testing stage it appeared that people responded inappropriately to some of the movies. For example, The Shining, originally meant to elicit fear, is so well known and by now so old, that people often show a smile of recognition instead of fear. Similarly, Drop Dead Fred caused people to be annoyed more than amused. To find out whether these two movies should be