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Eyebrow emotional expression recognition using surface EMG signals

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ABSTRACT

The main objective of this study is to recognize facial emotional expression effectively in human–computer interaction. A surface electromyography (sEMG) based eyebrow emotional expression recognition method is proposed. Using a specially designed headband, we conducted an experiment in which we recorded the sEMG signals from the frontalis and corrugator supercilii muscles of six participants who were instructed to pose the facial expressions of anger, fear, sadness, surprise and disgust. Subsequently, six features of the sEMG time domain were extracted and used as input vectors to an emotion recognition model based on an Elman neural network (ENN). The performance of this model was compared to another recognition model based on a Back Propagation neural network (BPNN). The average recognition rate for the five emotions achieved by the ENN-based model was 97.12% in the training and 96.12% in the test set, which was slightly superior to the performance of the BPNN-based model.

1. Introduction

There is an old Chinese saying: “Love can be conveyed by eyebrows”. Indeed, it appears that eyebrows are important facial areas for the recognition of emotions [1]. In recent years, human–computer interaction (HCI) has drawn attention to the voice, facial expression and posture as important perceptual interfaces in addition to the traditional keyboard and mouse. As a consequence, facial expression recognition and analysis have become important areas of affective computing [2,3]. Although much progress has been made, recognizing facial expression remains a difficult task due to the subtlety, complexity and variability of facial expressions [2].

Facial expressions can be classified into various ways, in particular in terms of prototypic displays such as the expressions of basic emotions [4], or as facial action units (AUs) as defined in the facial action coding system (FACS) [5]. Most HCI researchers have focused on detecting facial expressions with the aim of recognizing emotions [6,7]. Ekman and Friesen [8] proposed that six basic emotions (anger, disgust, fear, happiness, sadness, and surprise) are expressed in typical facial displays. Therefore, much research has focused on the detection of these basic emotions. Four of the six prototypical emotional expressions involve movement of the eyebrows (the FACS action units AU1, AU2, and AU4 [9,5]). According to emotion-FACS (EMFACS) [10], happiness and disgust are not associated with brow movements; however, empirically, eyebrow movements also occur in disgust [9]. Miener [11] even found that AU4 (brow knitting) is the most frequent facial reaction to disgusting stimuli. Eyebrow movements are also often found during expressions of happiness [12,13], but this action is not coded in the FACS manual. Thus, five of the six basic emotions proposed by Ekman (anger, fear, sadness, surprise and disgust) are associated with, partly distinct, eyebrow movements including raising the eyebrows, drawing them together, lowering the brows, and drawing the inner corners of eyebrows up.

Several methods have been proposed for the automatic recognition of facial expressions. The most common methods are based on computer vision [14]. According to the features used to detect facial expressions, these approaches can be categorized into geometrical feature-based and appearance-based methods [15]. For example, Chang et al. [4] defined 58 facial landmarks to extract geometric features of the eyebrows, eyes and mouth, whereas Gabor wavelets [16] and local binary patterns [17] are two representative appearance-based methods. Martin et al. [18] used AAM [19], which combines geometric and appearance features, to track facial deformations and capture the shape of facial expressions. Most research on the recognition and classification of human facial expression has used still full-face images [20,21]. In recent years, however, increasing attention has been devoted to the recognition of facial changes in dynamic scenes [22,23]. For example, Isard and Blake [24] proposed a time series state-space model parameterized by a tracking motion vector. Since then, probabilistic video analysis has gained increasing attention. However, computer-vision based methods have some drawbacks: The recognition performance depends on the quality of the images or

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videos and is vulnerable to factors such as camera angle, background and lighting [25]. In addition, most researchers have concentrated on the surface appearance of the face, which is only an indirect method for the detection of the underlying muscular changes [26].

In recent years, emotion recognition based on physiological signals has become a new research focus in the field of HCI. The physiological signals that have been most widely used include the galvanic skin response, heart rate, electroencephalography and electromyography [27–29]. Surface electromyography (sEMG) has so far mostly been used for the recognition of gestures, sign languages, and movements of upper and lower limbs [30,31]. However, the sEMG, which reflects to some extent the underlying neuromuscular activity [32], has also been found useful for the recognition of facial expressions [33]. Schmidt and Cohn [34] measured 195 spontaneous smiles from 95 individuals using facial EMG and found consistent activation of the zygomaticus major muscle. Thring and Mahlke [35] used facial EMG to measure minute changes in the electrical activity of the zygomaticus and corrugator, which were regarded as indicators of emotional valence (positive/negative). Compared to the computer-vision based method, the sEMG-based method has several advantages: it allows the non-invasive recording of muscle activity, senses muscle action directly, is sensitive to minute muscle movements, is largely uninfluenced by head movements, and provides non-visual information about facial expressions [25,36].

Previous studies using facial EMG have used multi-electrode setups. For example, Fridlund et al. [33] extracted multi-site full-face sEMG signals to detect self-reported emotional states, and Lapatki [37] recorded EMG signals from seven different perioral muscles. However, being covered with facial electrodes may hinder spontaneous facial expressions. Electrodes placed over the eyebrow area have the least negative effect on spontaneous facial expressions, as well as on other facial actions, such as looking, respiration, and eating and drinking. Therefore, it would be important to know whether emotional facial expressions can be detected with sufficient accuracy from sEMG eyebrow activity alone. The fact that basic emotions are associated with partly distinct eyebrow movements suggests that this might be possible. However, this question has not so far been explored [1].

This study proposes an sEMG-based method for the recognition of five basic emotional expressions from eyebrow movements. We designed a headband suitable for the collection of sEMG signals in the eyebrow area (the frontalis and corrugator supercilii muscles) and asked participants to pose the facial expressions of five basic emotions. Subsequently, we extracted six time domain indices of the sEMG signals and used them as input vectors to an ENN-based recognition model. In addition, we compared the performance of the ENN model to that of a BPNN-based model.

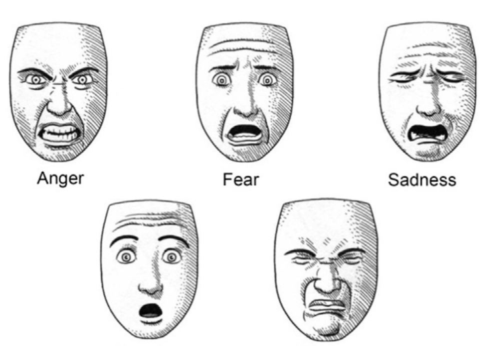

Fig. 1. The five eyebrow emotional expressions used in our study.

2. Materials and methods

2.1. Participants

Six men volunteered to participate in the experiment ($M=27.1$, SD=1.9, range 25–30 years). All participants had a medical examination to exclude possible facial musculoskeletal and nervous diseases. Before the experiment, the participants complete a questionnaire asking about height, weight and head circumference. Height ranged from 168 to 178 cm ($M=171.8$, SD=3.8), weight from 62 to 74 kg ($M=67.5$, SD=4.4), and head circumference from 55 to 59 cm ($M=56.9$, SD=1.4).

2.2. Eyebrow expressions and muscles

Of the six basic emotions of the Ekman set, happiness is not associated with brow movements [9,10]. Therefore, we limited our study to the expressions of anger, fear, sadness, surprise and disgust, which according to Ekman are universal across cultures [8,38]. Fig. 1 shows the images of five eyebrow emotional expressions used.

All facial expressions are produced by the coordinated movement of certain facial muscles [39]. According to previous research, the frontalis muscle, the corrugator supercilii and the depressor supercilii are the main muscles responsible for emotional expressions involving the eyebrows [5,40,41]. However, the corrugator supercilii and the depressor supercilii, which are responsible for eyebrows drawn medially and down, respectively, are too close to each other to be separately measured by surface EMG. Therefore, only activity over the corrugator and frontalis muscle was measured. To place the electrodes accurately and conveniently, we chose to measure activity over the left frontalis and the right corrugator supercilii. The locations of the electrodes are shown in Fig. 2.

2.3. Hardware

To allow an easy, accurate and standardized measurement of the sEMG signals of eyebrow movements, we designed a headband (Fig. 3) consisting of crossed elastic straps. The front strap was used to attach the electrodes for the EMG measurement, and the top strap was used for the fixation of the headband and the EMG cables. An additional adjustable strap was placed in the back to allow the flexible adjustment of the headband.

To allow a standardized and convenient measurement of the sEMG signals, the headband has six snap electrodes attached to the EMG cables.

The sEMG signals were collected, amplified and transmitted using a 10-channel digital EMG system (FlexComp Infiniti System, Thought Technology Ltd., Canada). The sensors (MyoScan-Pro sensor) are able to detect sEMG signals from 0 to 1600 μV within

Fig. 2. Locations of the electrodes [19].