Automatic Emotion Recognition Based on Non-Contact Gaits Information

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INTRODUCTION

In recent years, emotion recognition has become a hot topic in human-computer interaction. If computers could understand human emotions, they could interact better with end users (Peter & Beale, 2008). In psychology, emotion is defined as a complex state that consists of a subjective experience (how we experience emotion), a physiological response (how our bodies react to emotion), and an expressive response (how we behave in response to emotion) (Smith & Lazarus, 1990). Emotion expression includes not only facial expression but also vocal and postural expression. The observable aspects of emotion (physiological and expressive components) might be able to be used as indicators of emotional state, such as facial expressions, speech, physiological parameters, gestures, and body movements (Peter & Beale, 2008). As the common use of modalities to recognizing emotional states in human-human interaction, various clues have been used in affective computing, such as facial expressions (e.g., Kenji, 1991), physiological signals (e.g., Picard,

Vyzas, & Healey, 2001), linguistic information (e.g., Alm, Roth, & Sproat, 2005) and acoustic features (e.g., Dellaert, Polzin, & Waibel, 1996). Other than that, it is feasible to recognize specific affective states using gait.

To investigate how gait features are effective in characterizing and recognizing emotions, gait features were used for modeling to identify different emotions. By utilizing 59 participants' gait data with emotion labels, machine learning models are trained to detect individual emotion (Li et al, 2016).

BACKGROUND: GAIT AND EMOTION

Walking is one of the basic and important components for the body posture and movement, and psychological research found that affective states can be identified by gaits (Montepare, Goldstein & Clausen, 1987). People in different emotional states could walk in different speed and show different gait patterns (Strike, Mohiyddini & Carlisle, 2009). Human can perceive others' emotion from

gait or posture in daily life. For example, people in fear may shrink his shoulder, and sad ones might lower his head and walk slowly (Roether, Omlor & Christensen, 2009). Even when gait was minimized by use of point-light displays, which meant to represent the body motion by only a small number illuminated dots, observers still could make judgments of emotion category and intensity (Atkinson, Dittrich, Gemmell, & Young, 2004).

Since Montepare et al. (1987) firstly demonstrated that gait relates to emotions, there have been a lot of researches focusing on the relationship between gaits and emotions. Krieger et al. (2013) found that gait, cognition and emotion are closely related. Applying sparse regression, Roether et al. (2009) extracted critical emotion-specific posture and movement features depended only on a small number of joints. Gross et al. (2011) identified the movement characteristics associated with positive and negative emotions experienced during walking. Destephe et al. (2013) assessed the differences between the expression of emotion regarding the expressed intensity. Characterizing human walking patterns by some kinematic cues, Hicheur et al. (2013) produced the avatar animation whose emotions could be recognized by human observers. In particular, by using data mining technique, much research has been done to recognize emotions automatically by analyzing subjects' gait. The accuracy of classifying distinct emotional states was 60~89% (Janssen, Schollhorn & Lubienetzki, 2008; Hicheur, Kadone, Grezes & Berthoz, 2013; Gunes, Shan & Chen, 2015; Clark, Pua & Pua, 2012).

Recently, it has also been reported the application of Kinect in the medical field. Lange et al. (2011) used Kinect as a game-based rehabilitation tool for balance training. Yeung et al. (2014) found that Kinect was valid in assessing body sway in clinical settings. Kinect also performed well in measuring some clinically relevant movements of people with Parkinson's disease (Galna, et al., 2014).

MAIN FOCUS: NON-CONTACT GAITS INFORMATION

Two Issues of Gaits Information

By exploring the researches and experiments on identifying humans' emotions from gait, there are two main foci: one is the way of data acquisition, the other is the features for describing gaits. These two foci are very important to identify human emotions automatically. Some works used high-speed cameras to get a video of gaits (Das & Meher, 2013; Rokanujjaman, Hossain & Hossin, 2014). The collected gait data lacked of some information such as joints of subjects' ankles, shoulders, etc. Some works employed 3D motion caption systems including wearable devices. While these wearable devices could help us acquire gait precisely, subjects with wearable devices may be uncomfortable, and emotions may be affected while walking (Roether, Omlor, & Christensen, 2009; Karg, Kuhnlenz, & Buss, 2010). The situation may be even worse for some people such as elderly adults, children, and mental patients. Thus, it is very important to acquire gait data in the way of non-contact. In addition, the cost is another considerable factor. The gait information recording technologies such as marker-based motion tracking system had already made it possible to automatically recognize the emotional state of a walker (Karg, Kuhnlenz, & Buss, 2010), however, because of the high cost of trained person, technical equipment and maintenance (Pogrzeba, Loreen, Wacker, Markus, Jung, Bernhard, 2013), the application of these non-portable systems were seriously limited.

Microsoft Kinect

The Microsoft Kinect is a low-cost, portable, camera-based sensor system, with the official software development kit (SDK). As a marker-free motion capture system, Kinect could continuously monitor three-dimensional body movement patterns, and

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