Affective Recognition Using EEG Signal in Human-robot Interaction

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Abstract. TODO : this part is waiting to be rewritten.

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1 Introduction

Hitherto, mechanical arm, as a vital product in industry field, has been broadly used in medical, exploration, rescue field etc. However, the mistake operation caused by human error, which should have been avoided, is still one of the dominant reasons causing accidents. As we all know, the state of human has a close link to the cognitive state of human and in some degree emotion is the main reason causing the change of the cognitive state, therefore, one of critical ways to avoid huamn error in mechanical arm operation is recognizing the emotion during the opreration process through detecting the physiological signal. Since R. W. Picard has defined Affective Computing (AC)[1] in 1995, affective computing has been a critical field in human-computer interaction area. such as Blood Volume Pressure (BVP), Skin Conductance Response (SCR), Respiration (RESP), Electrocardiogram (ECG), Electromyogram (EMG), Electrocorticogram (ECoG), Electroencephalogram (EEG), Heart Rate (HR), Oxygen Saturation (SaO2) and Surface Temperature (ST)[2]. In all physiological signals, EEG is no doubt the most capable signal directly reflecting the brain activity. Therefore this paper chooses to use 32 dry electrodes EEG signal acquisition equipment to obtain EEG signal data during mechanical arm operation.

There are lots of models which has been proposed to describe the emotion, such as six basic emotions model proposed by Ekman et al.[3], eight basic emotions model proposed by Plutchik[4] and the valence-arousal scale proposed by Russell[5]. For simplifing this problem, this paper chooses to use the valence in the valence-arousal model of Russell to evaluate the emotion of the subjects. And the valence reflecting the positive or negative aspect of the subjects is enough to describe the cognitive state of the subjects.

Besides the model of emotion, the way to obatain the ground truth of the subjects is also crucial. Almost all research in Affective Computing field use the self-assessment scores to estimate the true cognitive state of the subjects.

However, even the subjects themselves could hardly to retell the exact emotion state in the mechanical arm operation and using one single scores to estimate the cognitive state during the entire operation process is obiviously not reasonable in detail. So this paper proposes to use objective and real time indexes to represent the cognitive state of the subjects. In this paper, we record the track of the end point of the mechanical arm and extract the features of the track to represent the fluctuation of the cognitive state of the subjects. Meanwhile, we assume that the workload and the time pressure could stimulate the emotion change of the subjects, so we give a basic score, which reflects the emotion state the subjects should be, and add the weighted features scores to the basic score to reflect the fluctuation of the emotion state.

In our experiment, we designed three levels of operating tasks in different difficulty to stimulate the emotion state change. And the level of difficulty is determined by the workload and the time pressure. To eliminate the influence of unfamilarity, one minute of free exploration is added before these three tasks and to eliminate the interaction of different tasks, a 30 seconds reset time interval is added between the different tasks.

During the data process part, because of the low signal-to-noise ratio (SNR), the disturbance of EMG signal and the electromagnetic interference, the raw data have firstly been filter to the 1-64Hz frequecy band[6]. After normalization process, different scales sliding window are induced in extracting features. Because of the real-time label we obtain from the track mentioned above, it allows us to consider the data in single sliding window as one sample.

The feature extraction methods are detailed summarized in papaer[6], we choose three time domain features and one frequency feature to represent the raw data according to the value of the weighted relative occurrence. And at the feature selection process, we apply Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to select the extracted features above. And at the classification design process, we apply Support Vector Machine (SVM), which is a effective classification discriminator, to predict the emotion state.

Here is the remainder organization of this paper: Section 2 introduce the apparatus used in the experiment and the detail experiment protocol. Section 3 describes the data preprocess procedure, feature extraction, feature selection classification design methods. Section 4 focus on showing the data process results. Section 5 discusses the results. Section 6 gives the conclusion of our experiment.

2 Experiment Setup

2.1 Apparatus

There are 3 key equipment we use in our experiment: EEG Signal Acquisition Equipment, Mechanical Arm and Joystick. And there are 3 personal computer for communicating with EEG equipment, controling movement of mechanical arm through joystick and showing the end point of the mechanical arm.

EEG Signal Acquisition Equipment: The EEG Signal Acquisition Equipment we apply is the Cognionics HD-72 Dry EEG Headset(see in Fig. 1). Considering the difficulty of wearing EEG equipment and the comfort of the subjects, we choose 32 dry electrodes to obtain the EEG signal, which are showed in

Fig. 1.

2.2 Experiment Protocol

3 Data Process Method

3.1 Data Preprocess

3.2 Multi-scale Feature Extration

3.3 Feature Selection

3.4 Classification

4 Results

5 Discussion

6 Conclusion

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