

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 mistaken operation caused by human error, which should have been avoided, is still one of the dominant reasons causing accidents. As we all know, the performance of human has a close link to the cognitive state of human and to some degree emotion is the main reason causing the change of the cognitive state. Therefore, one of the 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. There are numerous physiological signals which could reflect the cognitive state of human, 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 have 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 obtain the ground truth of the subjects cognitive state 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 obviously 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 unfamiliarity, 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 frequency 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 paper[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 an 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 equipments we use in our experiment: EEG Signal Acquisition Equipment, Mechanical Arm and Joystick. And there are 3 personal computers

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*^[7] (see in Fig. 1). Considering the difficulty of wearing EEG equipment and the comfort of the subjects, we choose 32 dry electrodes, according to the international 10-20 system, to obtain the EEG signal, which are showed in Fig. 2. The sampling rate is 500Hz which is sufficient for obtaining EEG signal.



Fig. 1. Cognionics HD-72 Dry EEG Headset

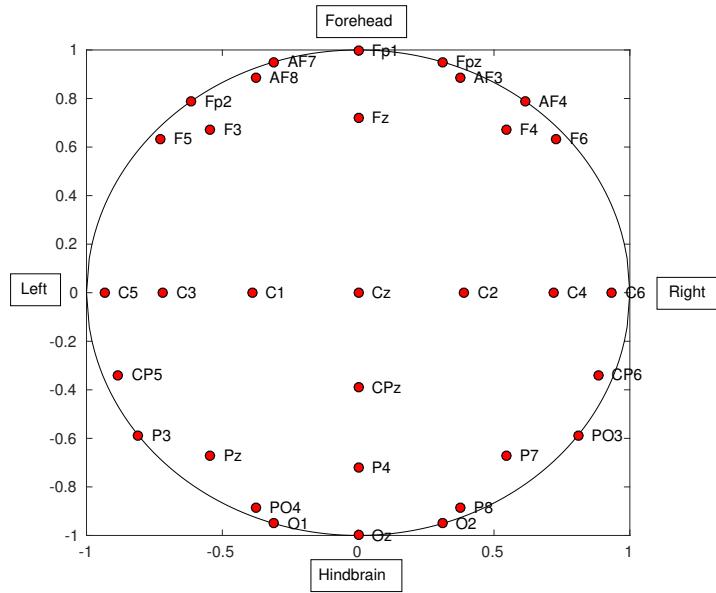


Fig. 2. 32 dry electrodes sensor location

Mechanical Arm: The mechanical arm we apply is the *Dobot Magician mechanical arm*^[8] (see in Fig. 3), because it supports reprogramming according to the need of users and the control precision (0.2mm) is adequate for our experiment.



Fig. 3. Dobot Magician mechanical arm

Joystick: The joystick we use is the flying joystick named *Extreme 3D Pro*^[9] produced by Logitech (see in Fig. 4). The perfect ergonomic design with a custom twist-handle rudder relies its one-handed control resulting in a smaller device footprint. There are six programmable buttons on the base. Each programmable button can be configured to execute simple single commands or intricate macros involving multiple keystrokes, mouse events, and more. In our experiment, we only operate the rocker in six basic direction movement, which are left-right direction, front-behind direction and left-right rotation.



Fig. 4. Logitech Extreme 3D Pro joystick

In our experiment, we use Robot Operating System (ROS) to receive the control signal from joystick, release the control signal to mechanical arm, receive the position information of the end point of the mechanical arm and record the track information with real time mark point in a sampling rate of 10Hz (code url: https://github.com/chenyuxuan/EEG_Human_Robot_Interaction).

<https://github.com/QCH1993/DobotMagician>). Meanwhile, real time EEG signal are recorded with mark information which could be used in subsequent time correcting process.

2.2 Experiment Protocol

Five healthy participants (two females, three males), aged between 23 and 25, participated in the experiment. Before all experiments, all participants were asked to have adequate sleepness.

In our experiment, firstly, participants were asked to read the experiment procedures and notes and the experimenter would read out the procedures and notes for a second reminder. And the experimenter was also present there to answer any questions. At the beginning of each experiment, one minute of free exploration were given to remove the interference caused by unfamiliarity. And then the subjects were asked to operate the mechanical arm to touch the different color point on the desktop according to a certain order. We designed three levels of operating tasks in different difficulty (easy, medium and hard mode) according to the number and position of points and the time constraint. In easy mode, the subjects were asked to touch three colored points without time pressure. In medium mode, the subjects were asked to touch five colored points without time pressure. In hard mode, the subjects were asked to touch five colored points in 90 seconds. To eliminate the interplay between the three tasks, a 30 seconds break time for resetting was added after each task.

The experiment enviroment is showed in Fig. 5. The Fig. 5(a) is the overview of the entire experiment environment. The subject operation platform (see in Fig. 5(b)) is insulated from the mechanical arm platform and all the information helping the subjects to move the mechanical arm was from three camera set around the mechanical arm and on the end point of the mechanical arm (see in Fig. 5(c)). The screen interface presenting the information from cameras are showed in Fig. 5(d).

3 Data Process Method

Traditional pattern recognition process includes 4 steps: data preprocess, feature extraction, feature selection and classification design. In this paper, we use several classic methods in these field to explore their performance in our experiment data.

3.1 Data Preprocess

For one subject experiment, the raw data are drawed in Fig. 6(a). And then according to the track mark and EEG signal mark, the EEG signal and the track were aligned in time. And we divided the entire EEG signal to easy mode, medium mode and hard mode procedure according to the mark information. The divided easy mode raw data, as an example, are showed in Fig. 6(b). Next,

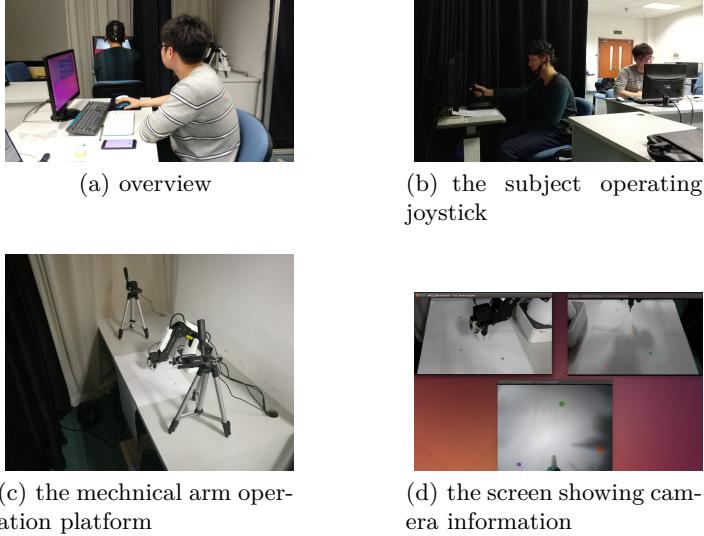


Fig. 5. The experiment environment

to remove the disturbance of EMG signal and the interference of various electromagnetic signal which are generally high frequency signals, we use band filter to filter out 1-64Hz signal, which are the dominant frequency band of EEG signal(see in Fig. 6(c)). Because the EEG signal has extra low SNR, the filtered signal at the beginning and end part is unstable. Therefore we selected to remove the first and last 5 seconds data (see in Fig. 6(d)). And for the computing convenience, the selected data are normalized to [-1,1] area according to all 32 channels signal by min-max normalization.

3.2 Multi-scale Feature Extraction

The feature extraction procedure

3.3 Feature Selection

3.4 Classification

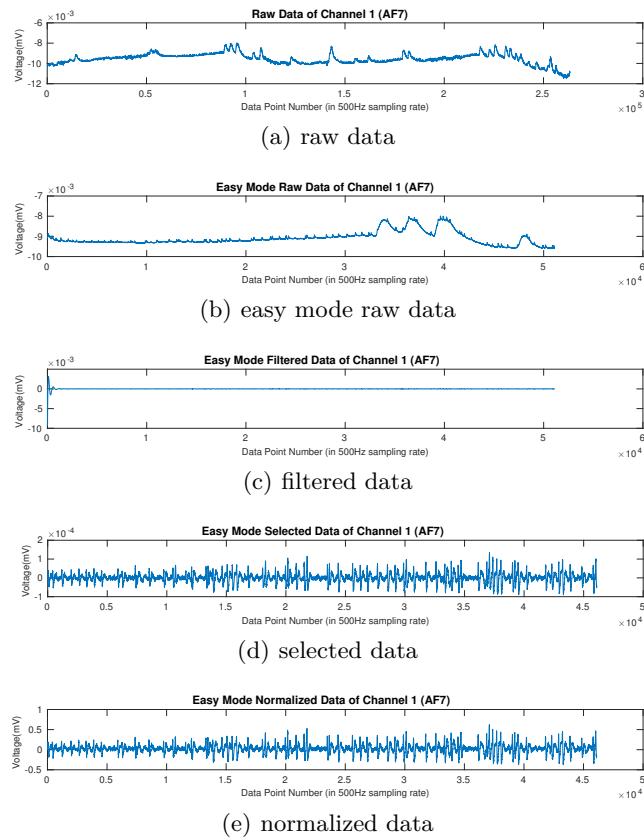
4 Results

5 Discussion

6 Conclusion

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**Fig. 6.** Data preprocess wave charts

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