2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

EEG-Based Emotion Recognition for Modulating Social-Aware Robot Navigation

Yuchou Chang, and Liang Sun, *Member, IEEE*

Abstract— **Companion robots play an important role to accompany humans and provide emotional support, such as reducing human social isolation and loneliness. Based on recognizing human partner's mental states, a companion robot is able to dynamically adjust its behaviors, and make human-robot interaction smoother and natural. Human emotion has been recognized by many modalities like facial expression and voice. Neurophysiological signals have shown promising results in emotion recognition, since it is an innate signal of human brain which cannot be faked. In this paper, emotional state recognition using a neurophysiology method is studied to guide and modulate companion-robot navigation to enhance its social capabilities. Electroencephalogram (EEG), a type of neurophysiological signals, is used to recognize human emotional state, and then feed into a navigation path planning algorithm for controlling a companion robot's routes. Simulation results show that mobile robot presents navigation behaviors modulated by dynamic human emotional states.**

I. Introduction

Companion robots have been investigated to relieve social isolation and loneliness [1,2]. When a human partner feels depression, a companion robot is able to apply interaction schemes and fights against human's constant feelings of sadness. Companion robots have shown promising prospects on caring people who need companion services. However, five ethical concerns have been raised for companion robots [3], in which personal privacy and freedom may be lost due to constant monitoring provided by a companion robot. Robot partners should not always give companionship, and humans have enough space for their personal freedom when they feel good without sadness feelings. Similar to therapy robots [4], companion robots are always-on-call for delivering companionship to human when they need emotional and social support. Robots respond to human emotional states and uses different interaction schemes for reducing human's sadness feelings. For this reason, real-time detection and interpretation of human mental states is critical to successful companionship when caregiving service is needed. Then, social-aware robots are navigated to human partner and companion service is given.

Mobile robot navigation has been guided by emotions to avoid obstacles safely and achieve goals fast [5-7]. To facilitate human-machine interaction in dynamic environments, Lee-Johnson et al. proposed a hybrid reactive/deliberative robotic architecture based on artificial emotions to support a robot's ability to adapt to dynamic conditions in navigation systems [5]. The proposed artificial emotion mechanism has boosted adaptive performance of navigation tasks with integrated control, path planning, and mapping, through comparing two measurements with emotions disabled and emotions enabled in mobile robots. A new navigation control system was proposed based on Affective Cognitive Learning and Decision Making (ACLDM) to safely avoid obstacles as well as speed up the learning process [6]. Learning and decision making are improved by incorporating emotion rewards in the reinforcement learning process, and therefore the capability of a robot's autonomous navigation is also effectively improved. A learning classifier system as a global search method was used to learn the bow-tie structure of an emotional reinforcer for adapting a robot's behavior [7]. The emotion system outperforms the default non-adapting navigation system.

In human-robot interaction (HRI), human emotional states have been detected and recognized by different modalities including facial expressions [8], voices [9], gestures [10], and physiological signals [11]. HRI performance can be promoted using robotic emotional behavior [12 - 15]. In this work, we proposed a neurophysiological signal-based emotion recognition for navigating mobile robots in a simulated environment. The dimensions of valence, arousal, and dominance [16] are used to recognize a human partner's emotion mental state and then a companion robot moves close to the human for companion service. The companion robot is not always to stay close with a human, since human privacy and enough space are needed. When a human feels sad, the companion robot moves to the human's position with recognized changes of human mental states. Robot navigation does not follow a shortest path as traditional path planning does, since a human may not feel comfortable due to privacy and enough space needed. Therefore, robot path and moving speed are determined by the human's emotion mental state, which is a dynamic process. For emotion-based robot navigation modulation, this is one of the first studies to apply electroencephalogram (EEG)-based brain signals for guiding robot motions, to the best of our knowledge.

The remaining of the paper is structured as follows. The related work is given in Section II. Section III presents the proposed emotional state recognition and robot navigation strategy. The experimental results and conclusion are given in Sections IV and V.

II. Related Work

A. EEG Classification in Daily Scenarios

Brain-computer interface (BCI) technology was initially used for medical applications [17] such as rehabilitation of

Yuchou Chang is with the Department of Computer and Information Science at University of Massachusetts Dartmouth, North Dartmouth, MA 02047 USA (phone: 508-999-8475; e-mail: ychang1@umassd.edu).

Liang Sun is with the Department of Mechanical and Aerospace Engineering at New Mexico State University, Las Cruces, NM, USA, 88003 (phone: 575-646-4368; e-mail: lsun@nmsu.edu).

stroke patients. Communication between human brain and external machines enables non-medical purposes [18,35] of BCI recently developed to have novel applications like workload monitoring and emotion recognition [19]. Different from the usage in laboratory environments, non-medical BCI needs dry electrodes, minimal calibration and user training, and portable data acquisition, so that mental state monitoring is feasible in daily scenarios. Non-invasive EEG-based BCI enables affordable and commercial data acquisition headsets to acquire brain signals in home or outdoor environments, and emotional data are collected with reduced restrictions in compared to the usage of expensive and non-portable EEG devices. For example, the DREAMER is the first database collected by low-cost, off-the-shelf, portable, and wireless devices, used in non-professional everyday life scenarios [20]. This builds an emotional communication way to enable humans and companion robots to interact with each other in daily life. Furthermore, for the purpose of convenient use in daily communication, single-channel EEG device is desired [21], since it is difficult to set up many electrodes on brain for a human subject who does daily activities.

B. Robust Path Planning for Navigating Mobile Robot

As a multi-objective problem, companion robot navigation not only provides companion support service to human partners, but also maintains social comfort to respect privacy and freedom of human partners. Based on its starting position and target positions, a robot plans its path based on environmental obstacles between its starting and target positions. For social-aware navigation, path planning algorithms can be divided into global planners and local planners [22]. An efficient global planner is the A* algorithm [23] that is deterministic by calculating distance between starting and target positions by minimizing the cost function:

$$f(n) = g(n) + h(n), \tag{1}$$

where $g(n)$ is the cost from the starting position to the current node, and $h(n)$ is the heuristic function with the cheapest cost from the current node to the target position. However, the A* algorithm suffers the limitation of discrete state spaces. The hybrid A* algorithm [24] improved the traditional A* algorithm by enhancing continuous nature of the search space in the real world. The hybrid A* algorithm has been successfully applied on robust navigation of autonomous robots in challenging unstructured outdoor environments [25], where the generated paths are guaranteed to be drivable by the vehicle.

III. Emotional State Recognition and Robot Navigation

A. The Proposed Framework

The framework of the proposed methodology is demonstrated in Figure 1. The social-aware robot detects the human's emotional state in a real-time mode. Based on dynamic detection of human emotions, the mobile robot may follow the previously determined path, speed, and direction to approach the human partner who feels sad. When the human has feelings rather than sadness and does not need any companionship, the robot will stay far away from the human for providing enough space and privacy [3].

B. Emotional State Recognition Using EEG Signals

Human emotions have been recognized by multiple modalities such as facial expressions, voices, gestures, and physiological data. As an innate neurophysiological signal, EEG-based emotion recognition cannot be faked or hidden, which is different from extrinsic indicators such as facial expressions. For this reason, EEG has been used for recognizing human emotions with multiple approaches [26 - 28]. In the proposed method, EEG is used to detect human emotional state, as an indicator to modulate the companion robot's navigation.

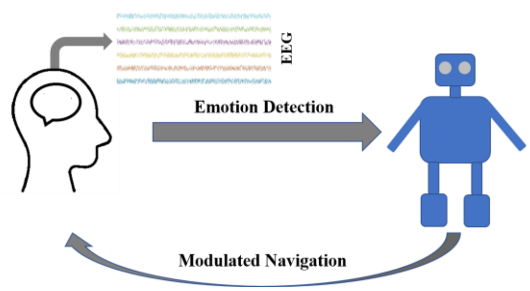


Figure 1. The framework of the EEG-based emotion modulated robot navigation.

In this simulated environment, human emotion is recognized based on the existing dataset DREAMER [20], since the proposed simulation on the DREAMER dataset enables emotion recognition to be implemented with cheap commercial, wireless, and off-the-shelf EEG headsets in everyday scenarios. DREAMER is different from other emotional EEG datasets such as DEAP [29] and MAHNOB-HCI [30] with non-portable devices for data acquisition in laboratory environments. In DREAMER, EEG data were acquired with a sampling rate of 128 Hz by the commercial Emotiv EPOC headset with 14 electrodes following locations of the International 10-20 system. Total 23 volunteers watched 18 film clips with 9 emotions: amusement, excitement, happiness, calmness, anger, disgust, fear, sadness, and surprise [20].

We identify the emotion sadness as the indicator of loneliness, and separate sadness from other 8 emotions as a binary classification problem for modulating robot navigation. To make the companion robot have suitable response time, we define a time window, *TW*, for detecting volunteer's emotional states. Power spectral densities (PSDs) are extracted in each time window to monitor emotional states, since it has been found that different bands in PSD features are correlated to human affective states [31]. Frequency bands of delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (13-30 Hz) are extracted and concatenated within 14 electrodes as feature vectors for classification. Although deep learning has obtained big success in past years, it does not appear to be effective for EEG signals classification, since EEG training data is limited [32]. According to this updated review, the shrinkage linear discriminant analysis (LDA) classifier [33] has been shown to be effective with little training data. The shrinkage LDA is applied in EEG classification for identifying emotional states, since training data is limited in existing EEG-based emotion recognition datasets. A regularization term is added to covariance matrix C of LDA:

$$\tilde{C} = C + \lambda I, \tag{2}$$

where I is the identity matrix and λ is the regularization parameter.

C. Modulated Navigation for Mobile Robot

To simulate a human-robot interaction in daily life, a human subject's EEG data and features are arranged in a sequential order that is corresponding to 18 film clips presented sequentially as shown in TABLE I of reference [20]. Each film clip related EEG stream is divided into multiple time windows, *TWs*, which are experimentally set as 20 seconds in the simulation environment. Since 2 film clips (film clip ID: 9 and 17 in the DREAMER) are related to sadness emotion, a modulation will be triggered if classification results in consecutive time windows are changed as:

$$Modulation = \begin{cases} E_{TW_n} \neq E_{TW_{n-1}}, & stwich\ direction \\ E_{TW_n} = E_{TW_{n-1}}, & continue\ to\ move \end{cases} \quad (3)$$

where the companion robot continues to move forward or backward when emotion is not changed from or to be sadness in two adjacent time windows. Otherwise, the robot moves toward the target position (the human partner's position) if $E_{TW_n} = Sadness$ and $E_{TW_{n-1}} = One\ of\ other\ 8\ emotions$. The robot moves backward to its original position and stay far away from the human partner who does not need companionship, when $E_{TW_n} = One\ of\ other\ 8\ emotions$ and $E_{TW_{n-1}} = Sadness$.

In the simulated navigation environment, a mobile robot locates in the corner of a living room, in which other obstacles including sofa, table, and TV are put in fixed positions. As shown in Figure 3(a), the mobile robot locates at the original position (green dot at the bottom right corner), where it waits for the response of the human partner's emotion changes. When the human feels sad, the mobile robot starts to move forward to him/her for providing companion service. If human's emotion is changed from sadness to other emotional states, the robot stops and reverses to the original place for delaying navigation time. The delayed navigation and companionship delivery are able to give the human enough space and privacy, since the human does not have sadness feeling and companion service is not needed. For reversing the direction of the companion robot, the hybrid A* path planning algorithm is updated by switching the target position (red dot on the right side of Sofa in Figure 3(a)) and the original position, based on which cost function $g(n)$ and heuristic function $h(n)$ are also re-calculated. To avoid collision with obstacles, a Light Detection and Ranging (LIDAR) [34] sensor is simulated to detect furniture locations and measure distances in the simulated living room. The LIDAR signals are presented as blue rays (3 blue regions of emitted lasers from the moving robot) as shown in Figure 3(b).

IV. Simulation Results

A. Emotion Recognition

The classification and robot simulation were implemented in MATLAB. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board. The classification results of emotional EEG data are presented in Figure 2. The shrinkage LDA using PSD features improves the classification accuracy of sadness emotion from 89.27% to 99.44% for all 23 human subjects. Shrinkage parameter λ is critical to LDA classification performance, which was automatically estimated by the cross-validation (CV) method, since it is impossible to manually tune shrinkage parameters during real-time EEG classification. The optimal value of parameter λ is determined by minimizing CV classification error for each time window of EEG data. It can be seen that classifications on different human subject emotional EEG data show different accuracies in Figure 2. This difference may be caused by non-stationary characteristics in EEG signals.

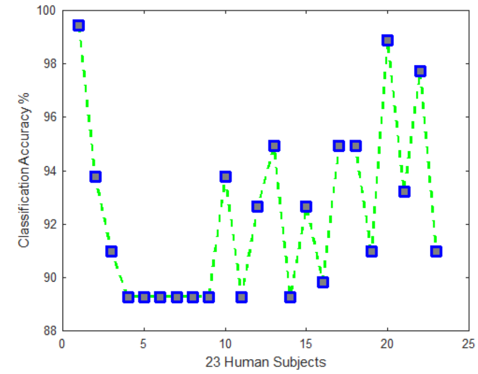
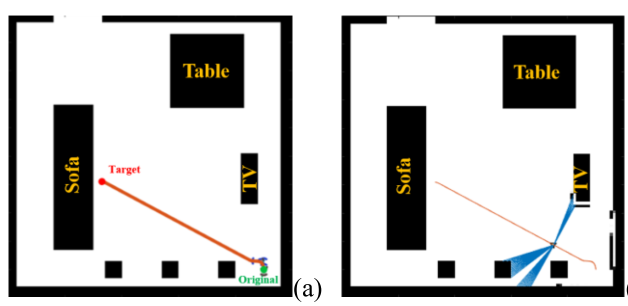
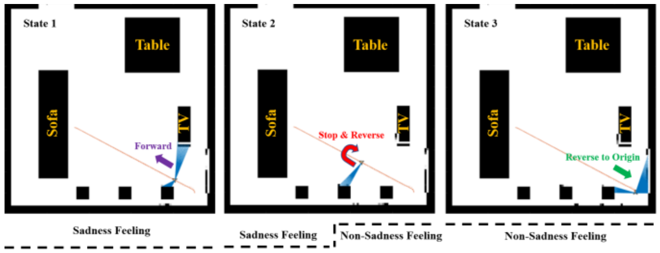


Figure 2. Classification results of emotional EEG data using shrinkage LDA and PSD features.

B. Simulated Social-Aware Navigation

The navigation is simulated in an indoor living room as shown in Figure 3(a). Some furniture including sofa, table, and television are positioned inside the living room. At the bottom of the living room map, there are three chairs with square shapes. When the human feels non-sadness and does not need any companionship, the mobile robot locates at the original position at the bottom right corner of the living room. Once the sadness feeling is detected from the human partner, the mobile robot starts to navigate based on the initial path of orange line as shown in the "State 1" sub-figure of Figure 3(c). Without any emotion changes indicated in Equation (3), the mobile robot is moving forward along the orange line to approach the human partner located at the target position shown as the red dot. If the human emotion is switched from sadness to other non-sadness emotional states, the mobile robot navigation is modulated and the previous moving forward direction is reversed back to the original position for delaying navigation process and companionship delivery, as shown in the "State 2" sub-figure of Figure 3(c). The mobile robot moves back to the original position if non-sadness feeling is not switched to sadness feeling, as shown in the "State 3" of Figure 3(c). This navigation delays companionship delivery and offer the human enough space and privacy before receiving the companion robot's service.





(c)

Figure 3. Simulation of the proposed EEG-based emotion recognition for modulating companion robot navigation. The initial path planning is presented in (a). Detection of furniture and measurements of distance by LIDAR (blue lasers) are shown in (b). In (c), switch of feelings from sadness to non-sadness enables the robot moves from forward direction to reversed direction until back to the original position, as shown in 3 sub-figures: State 1, State 2, and State 3. The dotted lines under the sub-figures represent EEG-based emotion detections with sadness (lower dotted line) and non-sadness (higher dotted line).

V. Conclusion

Robot navigation has been modulated by emotions for enhancing human-robot interaction performance in past years. In this work, mobile robot navigation is modulated by human emotions, which are recognized by brain EEG signals. Based on detection of human emotional states, the robot updates its navigation path, speed, and moving direction for delaying companion service and dynamically providing enough space and privacy for the human. In the simulated environment, mobile robot navigation is manipulated by dynamic changes of human emotions detected by neurophysiological signals. Since this work modulates robot navigation using EEG signals in simulation, future work will focus on real robot experiment using real-time Emotiv EPOC headset data acquisition and analysis.

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