Wearable Robot for Mental Health Intervention: A Pilot Study on EEG Brain Activities in Response to Human and Robot Affective Touch

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ABSTRACT

The theory of human touch that causes the body to release hormone oxytocin can be an effective treatment to alleviate depression and anxiety, such that the patients don't need to seek the help from consultants or drug medications to improve their mental conditions. In this paper, we have developed a wearable robot that mimic human affective touch to build social bonds and regulate emotion and cognitive functions. The touch-stimulated emotion can be measured by brainwaves from 4 EEG electrodes placed on the parietal, prefrontal and left and right temporal lobe regions of the brain. The novel Deep Learning emotion decoder has been designed to identify the human affective, non-affective and neutral emotions. It paves the way in the future to develop an intelligent self-adaptive robot that understands human emotions and adjusts its touch stimulation patterns accordingly to regulate human mental states and treat depression and anxiety problems.

CCS CONCEPTS

• Human-centered computing → Human computer interaction (HCI) → Interaction devices → Haptic devices

KEYWORDS

Affective Touch; Wearable Robot; EEG; Emotion Regulations

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1 Introduction

Depression and anxiety are common mental disorders. There are more than 300 million people of all ages suffer from depression globally [1]. Depression is different from usual mood fluctuations and short-lived emotional responses in everyday life. At its worst, it can lead to suicide if long-lasting and with severe intensity depression occurs. There are several therapies can treat for the symptoms, e.g., cognitive-behavioral therapy (CBT) works to replace negative and unproductive thought patterns with more realistic and useful ones; healthcare providers may offer medications with selective serotonin reuptake inhibitor (SSRI) and serotonin norepinephrine reuptake inhibitor (SNRI) [2]. Other methods, like Yoga, meditation or breathing exercise can also boost emotion and improve your body and mind healthiness [3].

Although there are known, effective treatments for depression and anxiety, fewer than half of those applied in the world (in many countries, fewer than 10% receive such treatments). Barriers to effective care include a lack of resources, lack of trained healthcare providers, and social stigma associated with mental disorders. To combat with such deficiencies of the treatment, in this research, we come up with the approach of using wearable robot with tactile stimulations to regulate human affective emotions. The patients can wear it all the times and the EEG (Electroencephalogram) recordings are used to interpret human emotions under our developed Machine Learning algorithm. As such the robot can adaptively change its stimulation patterns according to the human emotion state readings in real time.

2 Background and Related Works

2.1 Affective Touch Stimulations

Touch is the first of our senses to develop [4], setting the stage for one of the earliest maternal interactions [5], as well as being a necessary part of caregiving interactions [6][7]. Human touch has commonly been suggested to evoke a sense of "proximity and establish the human connection" [8].

Traditionally, touch tactile research has predominantly focused on the sensory-discriminatory aspects of touch [9], mediated by fast-conducting, large diameter Aβ fibers [10].

However, Olausson et al. [11][12] argue that humans have a tactile system working in parallel with the sensory-discriminatory system. This system appears to be related to the social and affective aspects of touch, and parts of this signaling are thought to be mediated by a group of C-afferent fibers [13].

C-tactile (CT) fibers are afferent, unmyelinated skin receptors that typically respond to stimuli similar to a light, stroking touch [14]. CT afferents exhibit an apparent velocity dependent firing frequency which also coincides with subjective pleasantness ratings in healthy humans [14][15]. The preferred velocity seems to reside between 1 and 10 cm/sec, giving rise to an inverted “U”, with lower CT-afferent firing and lower pleasantness ratings at slower and faster stroking velocities [14][15]. The “Affective Touch”, in particular, caress-like, slow velocity, gentle stroking touch, has recently been associated with the C Tactile (CT). And its well-studied positive affective value [16] has been shown to convey social support and intimacy with greater specificity than other types of social touch [17][18].

2.2 Emotion Recognition Using EEG Signals

Emotions are known as a group of affective states of human being arising as responses to stimuli from external environments or interpersonal events [16]. Using physiological signals, such as the electroencephalogram (EEG), body temperature (T), electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), respiration (RSP), etc., could reflect the un-mediated emotional status. Among all these physiological signals, EEG signals took advantages of time, spatial, frequency and asymmetric related characteristics, which can provide more rich information for emotion identification then other sensing modalities. In recent years, a high number of neuropsychological studies have reported correlations between EEG signals and emotions. There are two main areas of the brain correlated with emotional activity: the amygdala (projection of anterior insula) (located close to the hippocampus, in the frontal portion of the temporal lobe); and the pre-frontal cortex (covers part of the frontal lobe). Although there is no consensus about a possible lateralization of the amygdala, its activation seems to be more related to negative emotions than positive ones [19].

To understand more about the emotion related brain activities, we can divide EEG frequency domain measurement into five frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), gamma (30–80 Hz), and mu rhythm (8-13 Hz). Alpha waves are typical of an alert but relaxed mental state and are evident in the parietal and occipital lobes. Beta waves are indicative of active thinking and concentration, found mainly in frontal and other areas of the brain. Changes in alpha power and asymmetry between the hemispheres of the brain are related to emotions. A relative right frontal activation is associated with withdrawal stimuli or negative emotions, such as fear or disgust. A relatively greater left frontal activation is associated with an approach stimuli or positive emotions, such as joy or happiness. Thus, the asymmetrical frontal EEG activity may reflect changes on the valence [19][21]. Beta bands are also related to valence [21]. Pre-frontal and parietal asymmetry in the alpha band and temporal asymmetry in gamma band are present for valence recognition, while pre-frontal asymmetry in alpha band and temporal asymmetry in the gamma band are observable for arousal recognition [22]. Changes in the gamma band are related with the emotions happiness and sadness, and so is the decrease in the alpha wave in different sides of the temporal lobe (left for sadness, and right for happiness) [23], [24].

Moreover, a recent work [25] demonstrated that, following a tactile stimulation caressing in the range of 2-4 cm/s, a suppression of μ-oscillations (8-12 Hz, the idling rhythm of sensorimotor regions) in electrodes over the contralateral somatosensory cortex occurs.

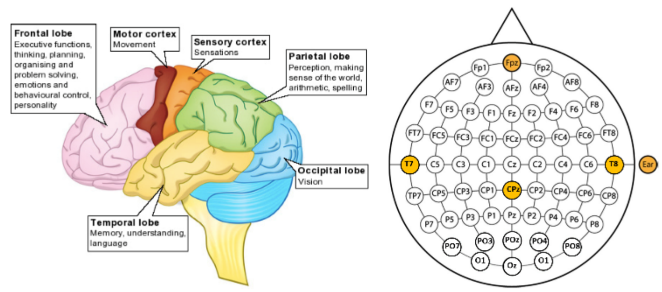

Figure 1: (Left) Brain regions: The cortex subdivided into the frontal, temporal, parietal, and occipital lobes. (Right) The interpretation of EEG 10-20 system: Our electrodes are attached on the left and right temporal lobe regions (T7) & (T8), central parietal lobe (CPz) and prefrontal lobe (Fpz).

2.3 Soft Pneumatic Actuator as Affective Touch Stimuli

Interactive, pneumatically-driven actuators made from pliable materials and inspired by soft-robotic principles [26] are emerging as new kind of tactile stimuli. Several studies used this type of actuators to investigate how such tactile sensations were perceived [26]-[28]. The pliable surface material, when deformed via pneumatic force enact tactile sensation through dynamic, seamless shape-changes against human skin. Such actuation affords a sensual quality resembling that of a human touch [26]. We refer such features as the “affective qualities” of the actuator. Such “affective qualities” lend soft pneumatic actuators comparable advantages to facilitate affective communication, then mechanical vibrators. Mechanical vibrators, although is currently the most widely used in wearable haptics design, have limitations in inducing pleasant sensations. For example, one study showed that their high frequency movements can induce negative sensations after lengthy exposure [28].

In an effort to simulate human affective touch, we have designed AffectNodes2, a soft wearable robot, which contains an array of pneumatic actuators and attempt to evaluate the sensations it induces. The actuators could be actuated in a sequence with a velocity of 5-38cm/s and an applied force around 0.5N.

3 Methods and Procedure

3.1 Experimental Protocol

We have recruited 7 participants aged 23~40 (5 males, 2 females) in our preliminary affective touch and EEG recording experiment. Participants were comfortably seated, and the left forearm was horizontally placed on the supportive cushion. For all trials, participants wore earplugs in order to prevent any auditory cues, and were restricted from watching the researcher, to ensure that the tactile stimuli were not facilitated by visual input and eliminate any anticipatory effect resulted from knowing the type of stimuli treatment in advance.

In the experiment, we used AffectNodes2 robot tactile interface, where we can arbitrarily adjust the touch stimuli patterns in different speed and normal forces applied on the wearer's skin. The velocity and force profiles were preliminarily selected as 6 cm/s and 0.5N to simulate the affective touch (which is based on the previous literature studies that the 6 cm/s will be the optimal speed of affective gentle touch, i.e., CT-Optimal touch), while 30 cm/s and 0.6 N are selected to generate the non-affective touch stimuli. In the meanwhile, the robotic touch was compared with real human touch to verify how successfully it can reproduce the bio-mimic, human-like touch, to ameliorate human's stressfulness.

We executed 7 different sessions of stimulation protocols among each participant: (Session 1) Relaxation: The participant was simply doing nothing but with his/her arm resting on the supportive holder and stayed still to establish the baseline. The entire session lasted for 3 min. (Session 2) Slow Brush Stroke: The participants received stimulations from a cosmetic make-up brush (Natural hair brush, No 7, The Boots Company) with the stroke speed of 6 cm/s, normal force of 0.5N, according to the setups of affective, gentle touch criteria (CT-Optimal touch). The entire duration lasted for 2 min executed by the researcher (experimenter). (Session 3) Fast Brush Stroke: The participants received stimulations from a paint brush with the stroke speed of 30 cm/s and normal force of 0.5 N. The entire session lasted for 2 min executed by the researcher. (Session 4) Slow Human Touch: The researcher simply used the hands to apply a gentle touch on the participant's forearm, again, with the speed of around 6 cm/s and normal force of 2 mN to generate CT-Optimal touch behavior with the duration of 2 min. (Session 5) Fast Human Touch: The researcher used the hand to apply a very rough touch on the participant's forearm skin, with the speed of 30 cm/s, and force 0.6 N to generate non-affective touch for totally 2 min. (Session 6 & 7) Robot Slow and Fast Touch: The participants wore our robot tactile interface and experience the aforementioned simulated affective touch and non-affective touch stimuli as described in the previous paragraph. Throughout the experiments, the stimulations were executed in constant intervals (slow speed: 6 sec; fast speed: 1 sec) repetitively. And between each interval, there was a 1 second resting state. The participants are also required to give feedbacks and ratings of emotion arousals and valence after each experiment session.

3.2 Data Collection and Analysis

For the whole experiments, brain signals were collected through the OpenBCI Cyton Biosensing Board (8-channels), with 250 Hz sampling rate and 24-bit resolution. The gold-plated (Au) cup electrodes were placed on the participant's head to measure EEG signals. To measure the most relevant emotion-related EEG signals, we put 4 electrodes on the scalp at standard positions T7, T8, CPz and Fpz (according to the International Standard 10-20 System) (Fig. 1), which correspond to the left and right temporal lobe, central parietal lobe, and pre-frontal lobe regions. The specific emotional responses can be found in these regions accordingly as described in Section 2. There is also one GND electrode attached on the left earlobe to provide the reference signal. We only use totally 5 electrodes to reduce the burden of the participants and make the wearable platform as compact as possible.

The finite impulse response (FIR) band pass filter of 1~50 Hz, and notch filter of 50 Hz and 60 Hz, with Hamming window being utilized, are to remove DC offset, power line interference and electrocardiogram artifact. The signals were then transformed into frequency domain by short-time Fourier transformation (STFT), with sliding window 1s (250 data points) and 80% time window overlap.

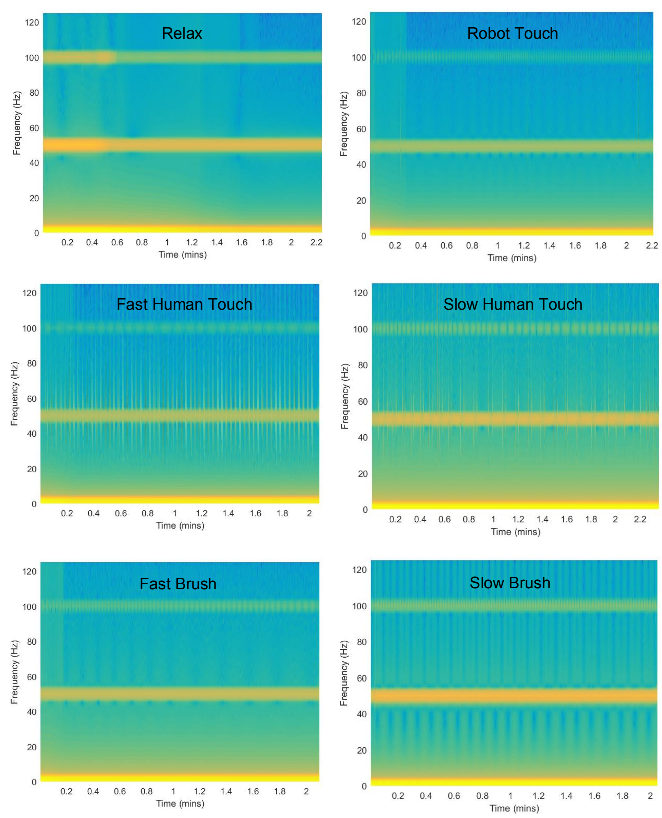

Figure 2: The 2D diagram of Short-Time Fourier Transform (STFT) of EEG signals collected from Parietal Cortex (CPz). It shows the EEG power spectrum evolution for the two minutes tactile stimulation session under different affective touches.

The affective touch induced EEG signals under different stimulation patterns were then compared at each electrode (4 aforementioned brain regions), by using STFT. Fig. 2 shows the STFT spectrogram at central parietal cortex (CPz) during the entire 2 min experimental session. We can observe that the slow human touch and slow brush stroke have obvious power attenuation, especially in the alpha and beta frequency bands, compared to other touch stimuli including the rest state. In contrast, the fast human touch and fast brush stroke have relatively higher arousal. To be noticed, there are some ripples in STFT spectrogram during the human touch (corresponding to the touch intervals), because whenever the human touches the skin, the peripheral nervous system (Aβ fibers) will deliver somatic sensation signals to notify the parietal lobe cortex, which is just captured by our electrode at CPz.

The data collected here at all 4 electrodes in the representation of power spectrum will be further utilized as training and testing dataset for our machine learning algorithm.

4 Deep Multi-spectrogram Convolutional Neural Network (Deep MS-CNN) for Emotion Recognition from Multiple Electrodes

To truly develop an intelligent wearable robot that can adapt to human's emotion and change the tactile patterns, we have to let the robot know what the human currently feels. As discussed above, a very important part of this paper is to develop an EEG-based emotion extractor for multiple electrodes that is trainable, producing informative representations for recognition and retrieval touch-stimulated emotions, and is efficient to compute.

Our approach is to learn to combine information from multiple spectrograms collected and transformed from each electrode using a unified CNN architecture that includes an emotion extraction layer (Fig. 3). All the parameters of our CNN architecture are learned discriminatively to produce a single compact descriptor for the emotion. The spectrograms are generated under the aforementioned STFT technique with Hamming sliding window with 80% overlap of the time-series data (250 frequency components, i.e., $R^{250\times1}$ vector, after the transformation). We keep collecting the data until we collect 250 vectors, and obtain a spectrogram image with the size of 250×250 matrix. Notably, as long as we keep collecting the data using the sliding window strategy, we will get as many spectrogram images as possible. These spectrogram image will constitute the training and testing samples of our machine learning algorithm.

Emotion Descriptors:

The emotion descriptors we consider here is the CNN activation features. For our CNN features we use the VGG-M network from which consists of mainly five convolutional layers conv1,...,5 followed by three fully connected layers fc6,...,8 and a softmax classification layer. The penultimate layer fc7 (after ReLU non-linearity, 4096-dimensional) is used as emotion descriptor. The network is pre-trained on ImageNet, and then fine-tuned on all 2D spectrograms of the EEG signals in training set.

Multi-spectrogram CNN:

Here, we focus on the problem of learning to aggregate multiple spectrogram in order to synthesize the information from all views into a single, compact emotion descriptor. We design the multi-spectrogram CNN (MS-CNN) on top of spectrogram-based CNNs (Fig. 3). Each spectrogram observed from each electrode is passed through the first part of the network (CNN1) separately, aggregated at an emotion extraction layer, and then sent through the remaining part of the network (CNN2). All branches in the first part of the network share the same parameters in CNN1. We use element-wise maximum operation across the spectrogram in the emotion extraction layer. An alternative is element-wise mean operation, but it is not as effective in our experiments. The emotion extraction layer can be placed anywhere in the network. We show in our experiments that it should be placed close to the last convolutional layer (conv5) for optimal classification and retrieval performance. Emotion extraction layers are closely related to max-pooling layers and maxout layers, with the only difference being the dimension that their pooling operations are carried out on. The MS-CNN is a directed acyclic graph and can be trained or fine-tuned using stochastic gradient descent with back-propagation.

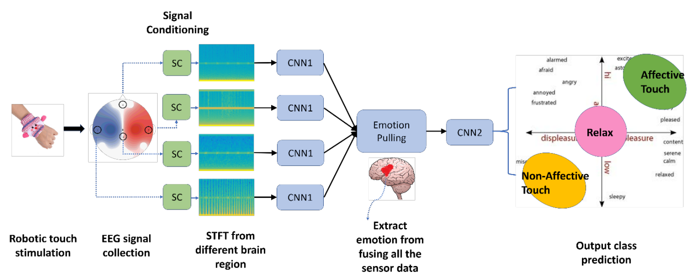

Figure 3: Deep Multi-spectrogram Convolutional Neural Network (Deep MS-CNN) structure for touch-stimulated emotion extraction.

Performance Evaluation:

We separate the training data sets into 3 categories: Affective touch, Non-affective touch and relaxation. The affective touch constitutes all the touch stimuli which satisfy the affective touch condition (i.e., speed: 6 cm/s; normal force 0.5 N) (including slow human touch, slow brush stroke and robot slow touch), while non-affective touch comprises all the other touch stimuli not satisfying the conditions (including fast human touch, fast brush stroke and robot fast touch). And we use the data collected in the relaxation session as the relaxation training data sets.

The training progress diagram and confusion matrix can be seen from Fig. 4. It shows fast convergence rate when reach to the stable identification accuracy, which is around 97%, to identify affective touch, non-affective touch and relaxation states. The true positive rate to identify each classified touch category is also significantly higher than the false positive rate.

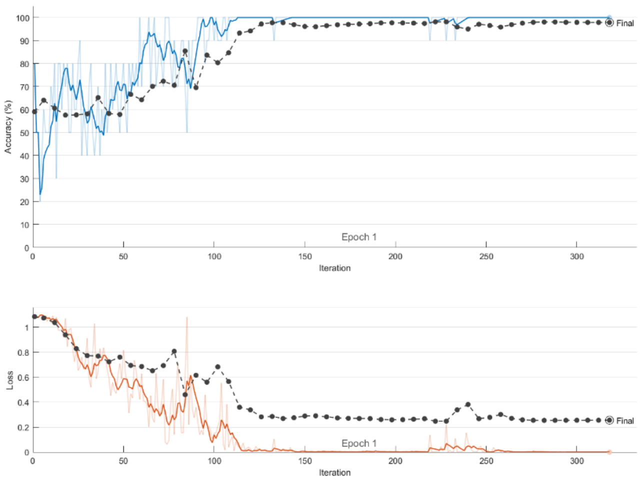

Figure 4: Training progress diagram.

5 Conclusion and Future Works

The research work conducted in this paper is to establish a fundamental building bock to develop a high accuracy emotion extractor to let wearable robot understand human touch-stimulated emotions by EEG measurements. The developed learning framework can easily span to more electrodes attached on the human brain identify different emotion or cognitive behaviors. The power spectrum frequency band analysis demonstrates the feasibility that our robot tactile device and effectively reproduce the biomimic, human-like touch stimuli.

In the future, more human subject trials will be recruited to collect more quantified emotion labels in order to provide precise emotion mental states recognition under our Deep MS-CNN framework. Also, the adaptive affective control algorithm will be investigated to change the stimulation patterns of the robot. Hopefully it can be easier to steer the mental states and regulate human emotions to treat patients suffered from depressions and anxiety problems.

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