CP-Robot: Cloud-assisted Pillow Robot for Emotion Sensing and Interaction

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Abstract. With the development of the technology such as the Internet of Things, 5G and the Cloud, people pay more attention to their spiritual life, especially emotion sensing and interaction; however, it is still a great challenge to realize the far-end awareness and interaction between people, for the existing far-end interactive system mainly focuses on the voice and video communication, which can hardly meet people's emotional needs. In this paper, we have designed cloud-assisted pillow robot (CP-Robot) for emotion sensing and interaction. First, we use the signals collected from the Smart Clothing, CP-Robot and smart phones to judge the users' moods; then we realize the emotional interaction and comfort between users through the CP-Robot; and finally, we give a specific example about a mother who is on a business trip comforting her son at home through the CP-Robot to prove the feasibility and effectiveness of the system.

Key words: Emotion sensing, ECG, smartphone, CP-Robot.

1 Introduction

With the development of physical world through various technology advances on Internet of Things (IoT), 5G and clouds, etc., more and more people start to shift their concern on their spiritual life [1, 2, 3, 4]. Using cloud-based solutions has been dramatically changing industrial operations in multiple perspectives, such as environmental protection [5], mobility usage [6], and privacy [7]. Though voice and video communications among people are convenient nowadays, the feeling of face-to-face communications with emotion interaction is still hard to be obtained, especially when people miss their families and friends during their working or sleeping time [8, 9]. On the other hand, the future 5G communication systems have higher and higher transmission rate which provide the basis to support the emotion interaction by remote communications [10]. As we know, traditional phone and video call are lack of emotion interaction and body contact, people who need special emotion care may not be satisfied with the experience of verbal based communications [11, 12]. For example, people always on business trips or taking some special job, such as sailor, easily feel lonely and need more interactions with family members rather than simple voice communications [13, 14]. So it is essential to design a method of enabling communications with more authentic feeling through conventional mobile phone and some new device [15, 16, 17, 18, 19].

As one method for human computer interaction, the interaction through robots is attracting more and more attentions [20, 21, 22, 23]. In this paper, we specially consider pillow robot for emotion communications due to its intrinsic features of low cost and convenience to carry. In the past, the functions of pillow robot are simple. Usually, a pillow robot is used for entertainment by simulating human's heartbeat by vibrator or body temperature through tiny heater. By comparison, this paper investigates the efficacy of pillow robot for monitoring user's health status and comforting user's emotion. To verify our idea, a new type of pillow robot will be built up [24]. The design goal of such pillow robot is to outperform existing ones in terms of intelligent interaction with user, physiological data collection, integration with cloud system, emotion detection, etc.

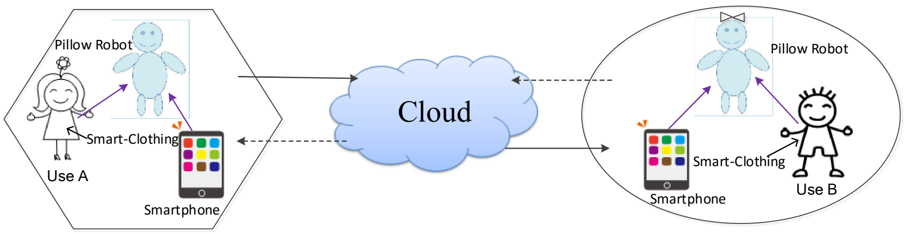
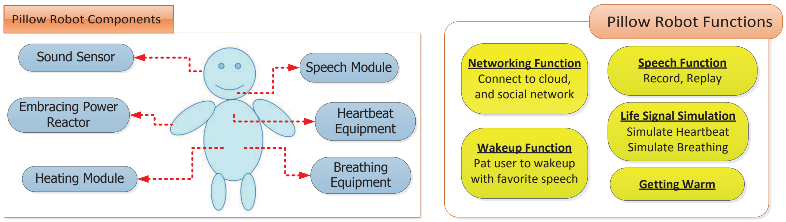


Fig. 1. Illustration of CP-Robot for emotion sensing and interaction.

The novel pillow robot is called as Cloud-assisted Pillow Robot for Emotion Sensing and Interaction (CP-Robot). Compared with traditional pillow robots, the CP-Robot relies on wireless signals for communicating with its user (i.e., CP-Robot owner, denoted as User A) and remote partner (i.e., the subject who holds the other CP-Robot, denoted as User B). Let CP-Robot A and CP-Robot B denote the pillow robots held by User A and User B, respectively. First, the pair of CP-Robots collect the body signals of both User A and User B. When the two users call each other, their CP-Robots work as smart phones. Additionally, users' body signals are transmitted to cloud via CP-Robots for emotion detection. Then, the data associated with User A's emotion is sent to CP-Robot B.



(a) Illustration of functional components.

(b) Illustration of functions of CP-Robot.

Fig. 2. Illustration of CP-Robot.

Likewise, CP-Robot A is also aware the emotion status of User B, as shown in the Fig 1. Through specially designed functions such as embracing forces, heartbeats, sounds, and temperatures, CP-Robot A mimics User B's behavior and emotion, while User B can imagine a touchable partner by considering CP-Robot B as User A. Therefore, CP-Robot brings people a sense of interaction. Inside the pillow, there are several sensors which may have the perception of different external factors and corresponding feedback devices, including heating device (simulating body temperature), vibration device (simulating the heartbeat), sound playing device (calling), and air pump (simulating embrace). The related sensors include the embracing force detection sensor, heartbeat detection sensor, temperature detection sensor, and speech signal detection signal on human beings. Fig. 2 shows the appearance and function modules of the CP-Robot.

Most of the traditional interactive robots focus on human-robot pair, that is, realizes the interaction between human and robot [25]. By comparison, CP-Robot achieves the emotion interaction between two persons geographically separated. In past years, some work designed remote emotional interaction system based on smart phone [26]. However, the emotional interaction is only through swinging the arms to show each other's feelings, without involving more health monitoring and emotional interaction. In the design of CP-Robot, the system not only enables User A to feel the heartbeat and body temperature of CP-Robot A, but also provides User A important feedback to sense the remote emotion and feelings of User B. Actually, in order to realize the functionality of emotion interaction in CR-Robot, two basic functions are also needed: 1) health monitoring and healthcare; 2) emotion detection. First, the prerequisite of emotion interaction is that the system can detect and recognize user's emotion accurately. Second, the body signals collected through wearable devices are important data sources for emotion detection.

Similar with body area networks and various health monitoring systems, there are three main components for realizing healthcare function of CP-Robot: 1) the internal sensors hidden in CP-Robot body collects environmental parameters around a user, and sense the user's body signals when he/she hugs the CP-Robot; 2) the sensor data is delivered to remote cloud via WiFi or through 3G/4G signals of a smart phone inserted into CP-Robot; 3) user's body signals stored in remote healthcare cloud will be utilized for health monitoring and remote healthcare. Since emotion interaction is based on emotion detection, which is a key challenge in the design of CF-Robot. In our design, we do not consider emotion detection through face video or audio, since the retrieval of those information is inconvenient for the user with various limitations. In this paper, we mainly use smart phone and Electrocardiograph (ECG) signals for emotion detection [27] [28], Some existing work advocate learning based on multi-modal data can improve the accuracy of emotion detection [29] [30]. In this paper, we use the data collected from the smart phone in the daytime and smart clothing at night, make feature extraction to the user's emotional data, and then the Continuous Conditional Random Fields (CCRF) is used to identify the user's emotion from the smart phone and the smart clothing, respectively. At last, we give user's emotion by decision-level fusion.

The main contributions of our research are as follows:

- We have designed CP-Robot system. The two sides can feel the other side's physical and emotional state, so as to realize the real interaction between people through the robot.
- We utilize the data collected by the smart phone and the ECG signal collected by the smart clothing to implement multimodal emotion detection.

The remainder of this article is organized as follows. The emotion sensing and interaction is described in Section 2. We set up one practical system platform in Section 3. Finally, Section 4 concludes this paper.

2 Emotion Sensing and Interaction

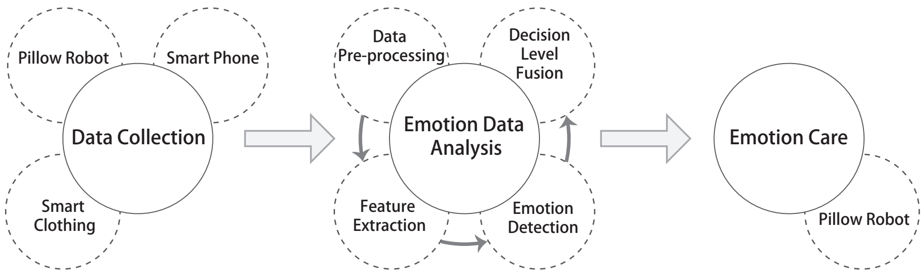


Fig. 3. Illustration of emotion sensing and interaction.

In this section, we give a detailed introduction about the emotion sensing and interaction in this system, and the emotion sensing and interaction are divided into 2 situations mainly according to whether the users hug the CP-Robot or not: (1) When the users hug the CP-Robot: if they wear the Smart Clothing, the CP-Robot is able to feel the users physiological signals (such as ECG Signals, temperatures, etc.), and thus realize the emotion sensing; if they do not wear the Smart Clothing, the CP-Robot feels the users' emotions mainly through the signals collected by the smart phones they carry with them; as for the CP-Robot, it can feel the users' hug strength, surrounding environment, etc., to realize the emotional interaction. (2) When the user does not hug the CP-Robot, just similar to the above, the robot feels the user's emotion mainly through the signals collected by the smart phone. When the robot discovers that the users are in bad moods, it can realize the emotional interaction through the pillows. To be specific, first, we collect information through the Smart Clothing, CP-Robot and smart phones; then we have the preprocessing and feature extraction about the data, make use of the characteristics on the Continuous Conditional Random Fields (CCRF) to have the emotion recognition, and give out the users' emotions on the basis of the decision-level fusion; finally, we realize the emotion care on the users through the CP-Robot, as shown in the Fig 3.

2.1 Data Collection

As for the users' data we have collected, we divide it into two kinds: 1) sensing data, namely the data collected by the CP-Robot, the Smart Clothing, and smart phones; 2) labelled data, mainly aiming at tagging people's emotions.

Recognition Data We make use of the CP-Robot, the Smart Clothing and smart phones the users carry with them to identify the users' emotions: the Smart Clothing is able to collect the users' ECG signals in real time, which are the major defining characteristics to judge the users' emotions; when the users hug the CP-Robot, it can not only feel the strength of the hug, but also realize the functions of the smart phones; the smart phones are able to collect some information such as the users' locations, living habits, etc. in real time. As for the emotion recognition, it is mainly based on the data collected by the Smart Clothing and smart phones. The following part mainly introduces the data collected by the Smart Clothing and smart phones.

- Smart Clothing The Smart Clothing, a kind of textile products with wearable flexible textile sensors integrated into them, is mainly used to collect the users' ECG signals without making them uncomfortable.
- Smart phone The smart phones mainly collect users' living habits as well as behavioral data, including their phone call logs, short message logs, application using logs, locations, accelerated speeds, etc., with the data being collected every 10 minutes.

In addition, the collected data also includes date and time of day, with the date including weekend, weekday and special day, and time of day including morning, afternoon and evening.

Label Data As for the tags of the emotion data, we make the users tag their own emotions through phones, with the emotional model used being the dimension affect model. As shown in Fig. 4, it is mainly divided into 2 dimensions: valence

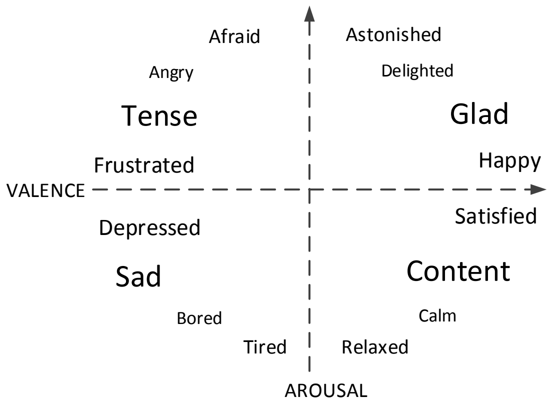


Fig. 4. The Circumplex model of mood: the horizontal axis represents the valence dimension and the vertical axis represents the arousal dimension.

and arousal, with the valence being from unpleasant to pleasant, and arousal from calm to active. Also, different valence and arousal are corresponding to different emotions. The users can label on the valence and arousal, and thus we can infer their moods. In this paper, we use several common and representative moods: M={happy, relaxed, afraid, angry, sad and bored.}.

2.2 Data Preprocessing and Feature Extraction

As for the data collected on the basis of the Smart Clothing and smart phones, we preprocess first and then extract the characteristics.

Data Preprocessing For the data we have collected, we need to process first, including the cleaning, integration and dimensionality reduction of the data, that is to say, we kick out some missing value, filter the noise in the ECG data, gather together some attributes such as the date, time and use conditions of the phones, and reduce the dimensions of some high dimensional data.

Feature Extraction based on the Data Collected by the Smart Phone First, we divide the data collected by the phones into 3 kinds: statistical data, time series data, and text data. 1)The statistical data includes the frequency that the users make phone calls, send short messages and use mobile applications during the data collection period. We can know their characteristics by counting the frequency. 2) The time series data mainly includes users' GPS data and accelerated speed data. Users' location information can be acquired according to the GPS data of their phones, and by using the DBSCAN clustering method, their visiting locations can be known; then we can judge whether the users are at home, in the office, or out of doors according to their tags; as for the activity data, we record the three-dimensional accelerated speed data x, y, z we have collected as a_x, a_y, a_z, and according to $s = \sqrt{a_x^2 + a_y^2 + a_z^2} - G(Gravity)$

as well as 2 set thresholds $threshold1$, $threshold2$, we can divide them into 3 situations: static ($s < threshold1$), walking ($threshold1 < s < threshold2$) and running ($s > threshold2$). 3) As for the collected text data, we extract the adjectives and nouns in the texts, and turn them into $[-1, -0.4] \cup [0.4, 1]$ by using SentiWordNet, and then the emotional characteristics in the texts can be acquired. We provide the main characteristics of the data collected on the basis of phones in Table 1.

Table 1. Smartphone Feature table

Data Style	**Data Type**
Activity level	Static, walking and runing
Location	Latitude and longitude coordinates User retention time
Phone screen on/off	The time screen on/off
Calls	No. of outgoing calls No. of incoming calls Average duration of outgoing calls Average duration of incoming calls No. of missed calls
SMS	No. of receive messages No. of sent messages The length of the messages Content of each SMS
Application	No. of uses of Office Apps No. of uses of Maps Apps No. of uses of Games Apps No. of uses of Chat Apps No. of uses of Camera App No. of uses of Video/Music Apps No. of uses of Internet Apps
Wifi	No. of WiFi siginals The time use Wifi
SNS	No. of friends Content post, repost and comment Image post, repost and comment Content or Image create time

Feature Extraction for the Date Collected by CP-Robot As for the ECG data we have collected through the Smart Clothing, we use the Convolutional Neural Network (CNN) to extract the characteristics of the continuous time series signals, with the CNN being introduced briefly below,

– *Convolution Layers*: Convolution layer includes a group of neurons to detect time sequence per unit time window or a part of per image, and the size of each neuron decides the area. Each neuron includes and inputs $\mathbf{x}$ with the same number of training weight ω, and a deviation parameter θ through an activation function s. In this study, logistic sigmoid function is defined as $s(x) = \frac{1}{1+e^{-x}}$, and the output value is $\mathbf{y}$, which can be described as the following:

$$y_i = s(\mathbf{x} \cdot \mathbf{w}^i + \theta^i), i = 0, 1, \ldots, m. \tag{1}$$

where m is the number of neurons. Each neuron scans input-layer sequentially, and then achieve feature mapping after neurons go through convolution. The original signals are strengthened and noises are reduced after the neuron goes through a convolution.

– *Pooling Layers*: Once the feature mapping generates, we adopt pooling function to conduct independent sub-sampling. Usually, average value and maximum value are commonly used pooling functions, in this study, we adopt average pooling. The dimensionality of convolution layer is greatly reduced, and overfitting is avoided as well.
– *Convolutional auto-encoder*: Auto-encoder is a kind of unsupervised learning method, whose goal is to learn one representation method for compression and distribution of data set. In this study, we will train all convolution layers by convolving the auto-encoder

In this paper, we use three-layer convolution and three-layer pool layer to extract the characteristics of the ECG signal.

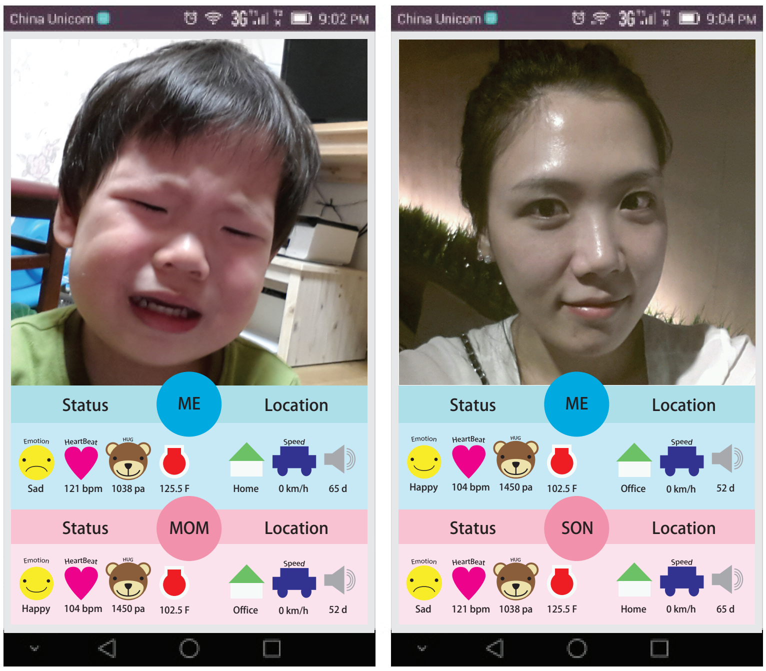


Fig. 5. Function Graph of APP for emotion sensing and interaction CP-Robot System.

2.3 Dimensional Emotion Detection

We use Continuous Conditional Random Fields (CCRF) [31] to identify emotions. CCFR is a kind of undirected graphic model, which has preferable results on the tagging and segmentation of the time series [29]. Since we have extracted the characteristics of the time series, we record them as $\mathbf{X} = \{\mathbf{x_1}, \mathbf{x_2}, \cdots, \mathbf{x_n}\}$ to show the input characteristic value, n to show the quantity of the time quantum of a series, and $\mathbf{y} = \{y_1, y_2, \cdots, y_n\}$ to show the corresponding tagged value of the n time series, so we can calculate the conditional probability as:

$$Pr(\mathbf{y}|\mathbf{X}) = \frac{\exp(\Psi)}{\int_{-\infty}^{\infty} \exp(\Psi) dy}. \tag{2}$$

where $\int_{-\infty}^{\infty} \exp(\Psi) dy$ makes the conditional probability turn into the normalization equation of 1, and Ψ is a potential function, with its definition being as follows,

$$\Psi = \sum_i \sum_{k=1}^{K1} \alpha_k f_k(y_i, \mathbf{X}) + \sum_{i,j} \sum_{k=1}^{K2} \beta_k g_k(y_i, y_j, \mathbf{X}). \tag{3}$$

where α_k and β_k are the parameters of the model, which provide the reliability of f_k and g_k. f_k is vertex characteristic function, which shows the dependency relationship between $\mathbf{x_{i,k}}$ and y_i. $\mathbf{x_{i,k}}$ means the kth element of the vector $\mathbf{x_i}$; g_k is edge feature function, which shows the relationship between the moods y_i and y_j predicted in the time quantum i and j. And f_k and g_k are given by the following formulas:

$$f_k(y_i, \mathbf{X}) = -(y_i - \mathbf{x}_{i,k})^2. \tag{4}$$

$$g_k(y_i, y_j, \mathbf{X}) = -\frac{1}{2} S_{i,j}^{(k)} (y_i - y_j)^2. \tag{5}$$

where $S_{i,j}$ is the similarity measurement, which describes the joint strength between the two peaks in the full connection diagram and has two types of similarities, with the definitions being as follows:

$$S_{i,j}^{(\text{neighbor})} = \begin{cases} 1 & |i - j| = n \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$S_{i,j}^{(\text{distance})} = \exp(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|}{\sigma}). \tag{7}$$

We use the stochastic gradient descent to train, and finally get the tag of the mood y according to the input characteristics.

2.4 Multimodal Data Fusion

When the signals collected by the Smart Clothing and smart phones exist simultaneously, we need to integrate the data. As for the integration problem of the data [32], we give out the integration on the basis of the decision-level, that is to say, we analyze the moods judged according to the mobile phone data and ECG signals together to figure out the users moods, with the specific definition being as follows: we define $y_s^{\mathbf{X}}$, $y_e^{\mathbf{X}}$ and $y_f^{\mathbf{X}}$ to show the moods judged according to the mobile phone data respectively, and as for the moods judged according to the ECG data as well as the both, they can be given out according to the following formulas:

$$y_f^{\mathbf{X}} = \alpha y_s^{\mathbf{X}} + (1 - \alpha) y_e^{\mathbf{X}}. \tag{8}$$

In this experiment, for the sake of simplicity, we mainly use ECG signals ($\alpha =$ 0.2) and obtain the users'cores from valence and arousal respectively to judge the users' moods.

3 A Demonstration System for Emotional Interactive

In this section, we have realized the CP-Robot with emotion sensing and interaction which is put forward in this paper. When the users hug the CP-Robot, the mobile phones inset in it will realize the video display between users during the holding time, and in order to make it more convenient for users, we have designed the popular and easy-to-understand cartoon interface. In this system, the mobile phone we have used is Samsung GALAXY Note, which has GPS, three-dimensional accelerations, WiFi and other basic functions. The system is realized on the Android System, with the CP-Robot and Smart Clothing coming from EPIC laboratory (http://epic.hust.edu.cn), and the cloud platform using Inspur SDA30000 [33], for this software is used to comfort the users. During our implementation process, we take the young mother comforting her child as an example, with the scenes being as follows: the mother Rachel is on a business trip in other parts of the country, and the child *Suri* is at home, missing her mother so much and crying sadly. Just as the picture on the left Fig. 5 shows, you can see the photo of *Suri* when having the real-time video chat: he is sad, as shown by the yellow head icon. The pink heartbeat icon means the heart rate, and *Suri* is in unstable mood, with the heartbeat being 121bpm, relatively high; *Suri*s hug strength on the pillow is 1039pa; *Suri*'s temperature is 125.5F; these are *Suri*'s status. As for *Suri*'s location, she is at home, with the movement rate being 0 and the surrounding noise being 65d. The picture on the right is the video photo when the mother is comforting *Suri*: the mother encourages *Suri* to be happy through her facial expressions, as the yellow head icon shows that *Rachel*'s emotion is happy, with her mood being relatively calm, and heartbeat being 104bpm, relatively normal. In order to comfort *Suri*, Rachel's hug strength on the pillow robot is 1450pa, relatively high. Rachel is in the office far away from *Suri*, with the movement rate being 0 and the surrounding noise being 65d. The experiment exhibits the effectiveness for user Rachel to comfort her child *Suri*'s emotion remotely through CP-Robot.

4 Conclusion

In this paper, we have designed CP-Robot system, which detects a pair of users' emotional status on the basis of the smart phones and the Smart Clothing assisted by the cloud. The Continuous Conditional Random Fields model is used to identify the users' emotion through the time series signals collected from the smart phones and Smart Clothing. In CP-Robot system, a user's mood status is transferred to the CP-Robot of the other person involved, making the pair of users be able to feel the true status of the other, which realizes the emotion sensing and interaction between people over long distance.

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