AIWAC: Affective interaction through wearable computing and cloud technology

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AIWAC: AFFECTIVE INTERACTION THROUGH WEARABLE COMPUTING AND CLOUD TECHNOLOGY

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ABSTRACT

To reduce the heavy burden from rapidly growing demands of healthcare service, wearable computing-assisted healthcare has been proposed for health monitoring and remote medical care. Although the provisioning of healthcare services can be significantly enhanced via wearable-enabled technologies, great challenges arise due to the lack of a human-centric mechanism for affective interaction. In this article, we propose a novel architecture, Affective Interaction through Wearable Computing and Cloud Technology (AIWAC), which includes three components: collaborative data collection via wearable devices, enhanced sentiment analysis and forecasting models, and controllable affective interactions. Based on the proposed architecture, we present our AIWAC testbed, design a practical mechanism for wearable computing-based emotional interaction, and discuss its open problems, which inspire potential research as a new direction.

INTRODUCTION

Due to the growing aged population coupled with limited medical facilities and healthcare in most developing countries, the traditional healthcare system meets challenging problems caused by its high operating cost and unscalability. Compared to the conventional healthcare system, a wearable computing-based solution is advantageous in many ways by upgrading the healthcare model from the traditional on-spot mode to in-home mode [1, 2]. The combination of wearable computing and cloud computing can further improve the quality of healthcare services by:
- Enhancing the quality of medical service informationization
- Increasing the utilization of medical resources by enabling remote medical services
- Promoting the development of the health industry

However, the existing system mainly focuses on healthcare service in a physiological aspect with the following two undesirable features.

Uncomfortable and negative psychological effects: Wearable body sensor devices might cause patients to feel uncomfortable, which further incurs stress and unhealthy emotions. In addition, the existing mode based on wearable devices for collecting physiological information might give users a negative psychological implication that they are currently in poor health. Especially when patients feel lonely or depressed, such a "conscious" way to collect and present their physiological information may result in more serious mental illness.

Emotional care deficiency: Lots of existing healthcare systems are targeted at caring for elderly people's physiological status. However, without efficient mechanisms of affective interaction, the traditional wearable technology is not adequate to provide advanced healthcare services involving both physical and emotional care, which becomes more and more important to improve seniors' quality of life. For example, currently, there are over one billion empty nesters in China. Due to long-time loneliness in addition to physical inconvenience, these empty nesters seriously suffer from negative emotions and various mental problems, which need emotional care to be provided.

Traditional affective prediction is usually via analyzing one type of emotional data in a single domain [3], which causes inaccuracy while creating difficulty in verifying the analysis results. To overcome this issue, this article designs a novel architecture named Affective Interaction through Wearable Computing and Cloud Technology (AIWAC), which considers the emotional data generated from multiple spaces (i.e., the cyber, physical, and social spaces — CPS-Spaces). AIWAC includes three components:
- A collaborative mechanism of multiple wearable devices based on weak deduction to collect sufficient data by limited resources such as hardware, energy, and bandwidth
- An enhanced sentiment analysis and forecasting model for multidimensional associated data from CPS-Spaces
- Controllable affective interaction based on the cognition of resource validity to implement synchronization between sensing and controlling

In the physical space, a user's physiological data is collected [4, 5], which includes various body signals, such as electroencephalography (EEG), electrocardiogram (ECG), electromyography (EMG), blood pressure, blood oxygen, respiration, and so on. In the cyber space, we

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utilize computer systems to collect, store, and transfer a user's facial and/or behavioral video contents. In the social space, the user's profile and interactive social contents are extracted to obtain social emotional requirements. With the development and technology convergence of social networking services (SNS), the Internet of Things (IoT), 5G networking [6, 7], and so on, the multidimensional affective data over the long term is considered as big emotional data [8]. First, the *volume* of data is big, especially for the user's video contents. On the other hand, emotion-aware applications require immediate service response (*velocity*) in order to guarantee the user's quality of experience (QoE), with a *variety* of devices in terms of perception, communications, and data processing. In this article, "big" emotional data is considered to possess the following features.

Tightly coupled correlation: Data from CPS-Spaces are tightly coupled, making it difficult to identify the relationships among the multidimensional data via traditional methods.

High-throughput content delivery: Traditional affective computing just focuses on some specific types of data without the requirement of high-throughput content delivery. It is a great challenge to transmit, process, and analyze big emotional data, which is difficult to manage via traditional affective computing methods.

Real-time analysis: Due to the dynamics of the affective state and behavior of human beings, the effective value of emotional data tends to attenuate over time; hence, real-time data processing and analysis are needed to accurately extract value from changing emotions.

Obviously, traditional affective computing can no longer meet these challenges for computation-intensive sentiment analysis and emotional interaction. Hence, AIWAC is proposed for representation, management, processing, and application of big emotional data, with an intelligently interactive mechanism and the capability of sensing users' physiological and psychological conditions. Furthermore, because human emotion is affected by subjective factors and cannot be quantified, it is difficult to verify the results of sentiment analysis, which is a critical issue in developing healthcare systems with AIWAC. In summary, several key applications will benefit from AIWAC.

Emotional care for empty nesters: The mental state of empty nesters is deducted by sensed emotion data, through which loneliness and other negative emotions can be alleviated.

Emotion monitoring for a long-term closed environment: Scientists working on deep-sea exploration and space exploration, as well as other specific areas, need to stay in a closed environment over a long period of time, running a high risk of emotional turmoil. Monitoring their emotions efficiently is beneficial for the successful completion of their tasks.

Affective disorder assistance: For example, people suffering from social autism with the shadow of social phobia can be assisted via sensing their abnormal mental states.

Rehabilitation aids: For patients who have just been discharged from hospital and are suffering from both physical and psychological pressure, personalized rehabilitation strategies based on physical information and emotional status can help them to recover faster with higher efficiency.

The remainder of this article is organized as follows. We introduce the AIWAC architecture and present the novel wearable computing-based acquisition of emotional data. We describe the big data analysis of multidimensional affective data, and show an emotional interaction based on AIWAC. We illustrate an AIWAC testbed for emotion-aware application based on a robot, and present the open issues and future work for AIWAC. Finally, we conclude this article.

AIWAC Architecture

AIWAC intends to build a new-generation intelligent emotion interactive system based on wearable devices, cloud computing [10], and big data to provide users with healthcare in both physiological and psychological aspects. As shown in Fig. 1, AIWAC is divided into three layers:

- The user terminal layer, including wearable devices for physiological data collection and cognized surrounding devices for emotion-aware action feedback
- The communication layer
- The cloud-based service layer

Now, we discuss the design details of these three layers.

User Terminal Layer

The user terminal layer consists of wearable and smart devices, wherein wearable devices are mainly used for collecting various physiological data, while smart devices provide a supporting user interface for emotional interaction. In general cases, the terminal is a wearable and smart device. In this article, we propose to use a robotic terminal to provide high-fidelity affective interaction and presentation; in particular, the robot is designed with an anthropomorphic appearance and human behavior patterns such as speech, smiling, nodding, walking, stretching arms and grabbing things, and so on.

Communication Layer

The communication layer consists of communication access and networking connection modules, where smartphones, computers, tablets, and any other smart devices with second-, third-, fourth-generation (2G, 3G, 4G), or WiFi access functions are integrated. With the support of the required software, these devices first receive various real-time physiological and psychological data, which are transmitted from the user terminal layer, and preprocess, format, and classify these data, including coding, decoding, filtering, and other operations. Then the preprocessed data are sent to the remote cloud.

Cloud-Based Service Layer

The cloud-based service layer is the core of AIWAC, which provides physiological and psychological data analysis via a data center on the cloud platform [9]. The data center is mainly responsible for data storage, feature extraction and classification, as well as individual emotion modeling. With the massive computing power of

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With the massive computing power of cloud-based services, AIWAC is able to efficiently respond to affective requests from the user terminal. In addition, AIWAC is able to provide public health monitoring based on the big scale of physiological and psychological data.

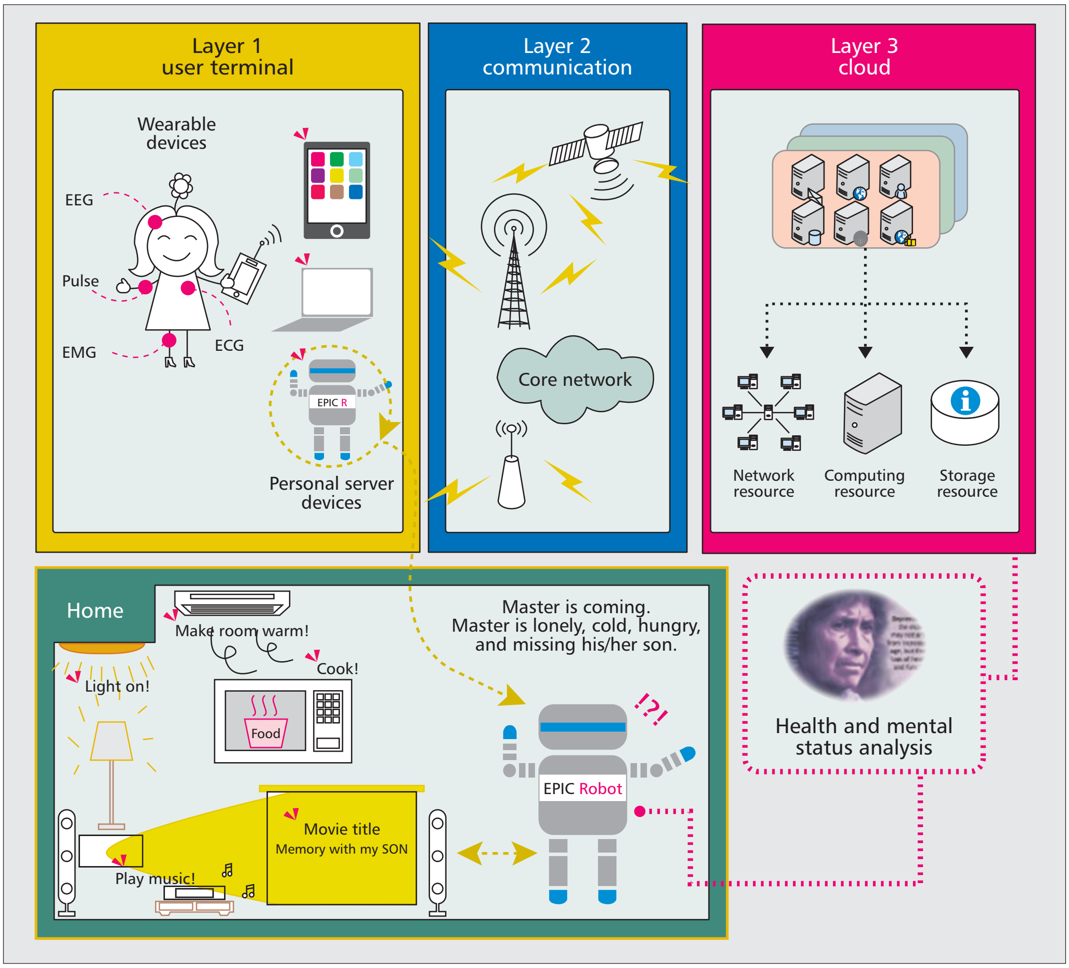

Figure 1. Architecture for AIWAC.

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Emotional Data Acquisition by Wearable Devices

The performance of affective interaction depends on the quality of collected data. The more types and larger-scale the emotional data are, the higher-accuracy emotional analysis results will have. However, it is difficult to fully meet the requirements for collecting emotional data with the limited resources of wearable devices. This bottleneck is caused not only by the limited number of devices, but also the limited energy supply for each device. In order to solve the contradiction between diversified data and limited resources, we investigate the control and collaboration of wearable computing-based acquisition of emotional data.

Figure 2 shows the proposed solution of the weak deduction-based multi-component collaborative sensing system of wearable devices, which aims to deactivate redundant devices sensing immaterial data. Specifically, based on the individual emotional model that is established by the analysis of big emotional data, only a small number of devices keep working to collect the most important data under normal conditions, while most of the other devices are in hibernation. Once emotional changes have been detected, more related wearable devices will be activated for data collection.

In order to select the key devices to keep being activated, we build a *Judgment Matrix*, that is, $A_{m \times m}$, to denote the relationship between m kinds of devices, wherein a_{ij} represents the relative importance of device i compared to that of device j. According to this matrix, the maximized eigenvalue λ_{max} can be calculated, and its corresponding normalized eigenvectors form a sorting vector W, through which we can know the importance of each device.

The framework consists of a wearable device layer, an emotional weak deduction receiving layer, and a cloud-based weak deduction layer, which are presented in detail below.

Wearable Device Layer

The wearable device layer includes various wearable devices, usually consisting of two modules: an acquisition module and a transmission module. For example, ECG, EEG, EMG, and other wearable devices can collect physiological data from users and transmit data to a server or other

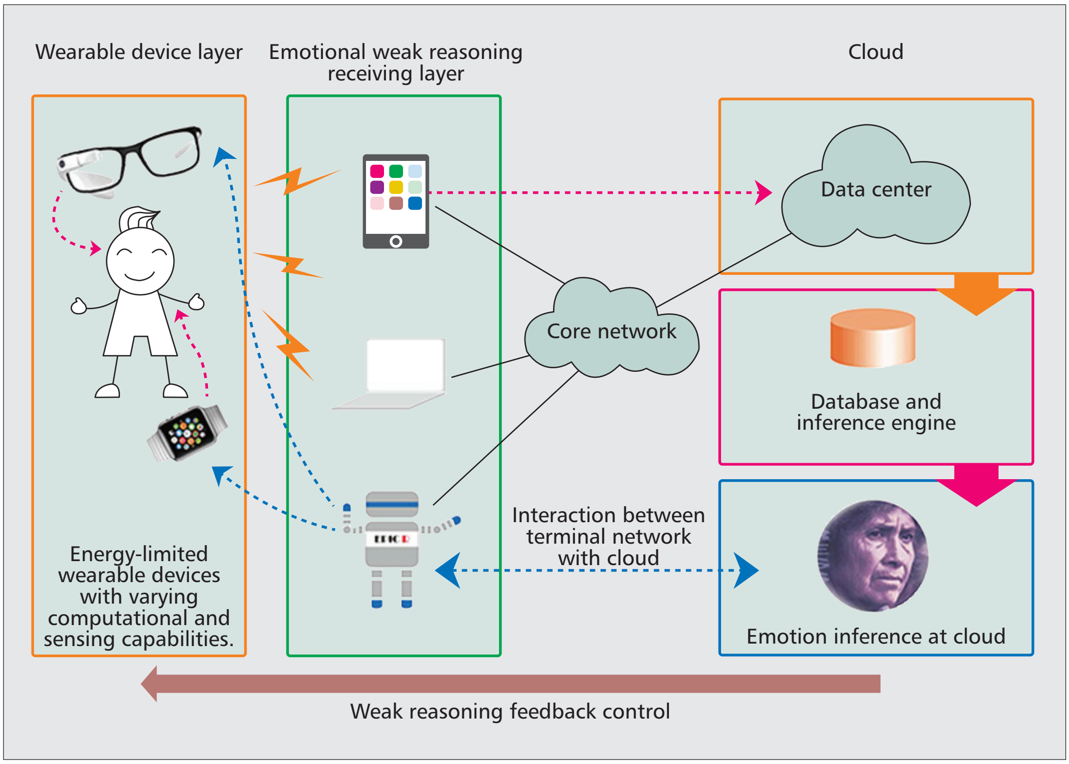

Figure 2. Architecture of the weak deduction-based multi-component collaborative sensing system.

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devices. The acquisition module is used to collect physiological data, while the transmission module is responsible for sending collected data to the sink node and receiving control signals. When the user is emotionally stable, only a few devices are activated to collect the key physiological data and monitor a user's emotional changes. Once a user's emotion fluctuates, the emotional weak deduction receiving layer sends a control signal to the wearable device layer and activates related devices for collaboratively collecting more data in order to improve the accuracy of sentiment analysis, or deactivates unrelated devices in order to save energy.

Emotional Weak Deduction Receiving Layer

Devices on the emotional weak deduction receiving layer can be either dedicated hardware, or mobile phones, laptops, or any other devices with communication capability, which are responsible for receiving and basically preprocessing data from wearable devices, sending collected data to the cloud, and feeding back the control signal to the wearable device layer based on the weak deduction results obtained by analysis in the cloud.

Cloud-Based Weak Deduction Layer

A user's emotional trends are dedicated in real time through emotional data analysis. Once a user's emotion fluctuates, weak deduction is enabled based on the existing emotional model to determine which devices are indispensable for data acquisition. Similarly, if the user is emotionally stabilized, unrelated devices are deactivated.

The weak deduction-based multi-component control mechanism of wearable devices is as shown in Fig. 3.

In particular, the core of this layer consists of the following components.

Vitals model: According to a user's physiological and psychological information in different emotions, a personalized vitals model is established for extracting features to provide a reasoning machine with support.

Reasoning machine: Once the reasoning machine receives physiological and psychological data fluctuation, it immediately deduces appropriate user emotional change based on the vitals model and pushes the result to the weak result receiver.

Weak result receiver: The weak result receiver activates some wearable devices to collect essential data for accurate affective computing and deactivates other unnecessary devices to save energy.

Big Data Analysis for Multidimensional Affective Data

Any data analysis method needs to be evaluated in terms of accuracy. However, it is difficult to verify the result of sentiment analysis since emotion is affected by subjective factors and cannot be quantified. Furthermore, traditional affective prediction is usually the result of analyzing a single type of emotional data, which causes inaccuracy and makes verifying the analysis results difficult. The single type of emotional data may be physiological data, social emotional data, facial video contents, or another type, which are typically collected in an isolated data space. Given the shortcoming of isolated data space oriented sentiment analysis, we consider the multidimensional affective data collected in CPS-Spaces.

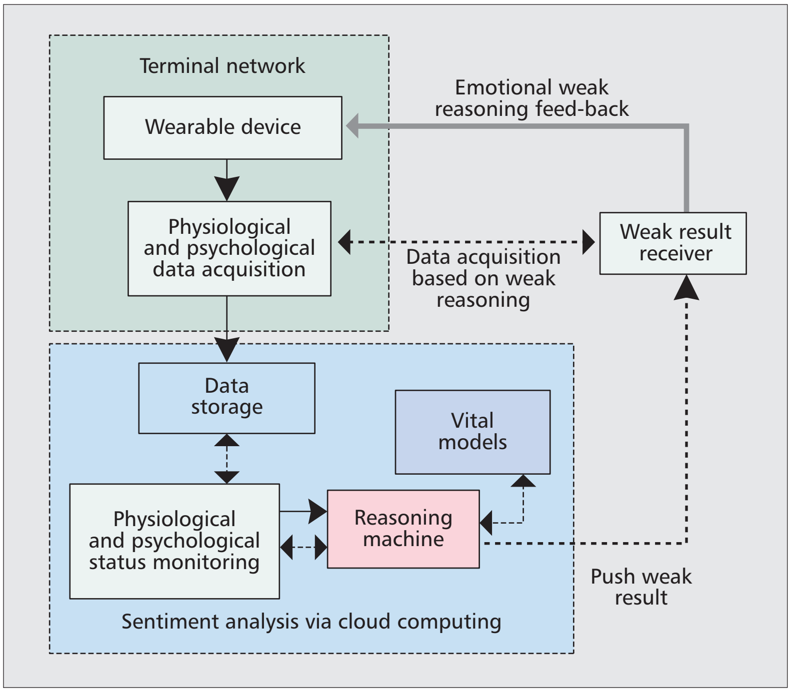

Figure 3. Weak deduction-based multi-component control mechanism.

Hybrid Big Emotion Data Analysis

According to the source data types, sentiment analysis in AIWAC can be divided into the following categories.

Physiology-based: Physical characteristics, bio-electricity signal characteristics, and behavioral characteristics are three major factors that reflect the affective state of human beings. Currently, a great number of studies investigate various methods of extracting and processing physical characteristics (including voice, posture, pupil, respiration, heart rate, body temperature, body characterization, blood pressure, etc.).

Video-based: By integrating the theory of multiple disciplines such as image processing, computer vision, computer graphics, artificial intelligence, machine learning, human brain cognitive science, optic neurophysiology, and psychology, sentiment analysis has become a multi-disciplinary research. Video-based sentiment analysis mainly focuses on visual features and multi-information fusion, mostly involving the image and video segmentation and cognition.

Text-based: Text sentiment analysis, also known as opinion mining, is to analyze, summarize, and reason the subjective text with emotional words. With the advent of a large number of subjective texts on the Internet and social networks, researchers have managed to gradually transit from simple word analysis to the complex analysis of emotional sentences and chapters.

Emotion-Driven Multidimensional Data Aggregation and Preprocessing

The accuracy of sentiment analysis and prediction depends on the diversity of the emotional data collected. Based on the emotion-driven multidimensional data aggregation, the verification model of sentiment analysis results can be enhanced.

Data Structure with a Time-Space Label — The aggregation of emotional data in CPS-Spaces can be formatted as key-value pairs, using a time-space label in the physical world as the key, and the social network data and physiological data as the value, as shown in Fig. 4a.

Affective State-Oriented Data Preprocessing — On one hand, unstructured data such as text, image, and video in social networks need a large storage space, while not all information contains valid emotional data; On the other hand, a large amount of various data are generated, including heart rate, blood pressure, body temperature, and other physiological data collected by wearable devices. Therefore, different data preprocessing methods are required for different types of data to clean invalid data, reduce redundancy, extract features, and compress size, as shown in Fig. 4b.

Emotional Change-Aware Data Aggregation — Emotional data in a social network has some properties of latency and discontinuity. Therefore, social network data and physiological data collected by wearable devices get out of synchronization, which makes their time-space labels mismatched. Hence, the direct integration of social network data and physiological data only through time-space labels will make the integrated data unable to accurately reflect a user's affective state, causing inaccuracy of the final analysis results. We popose a third-order tensor for data aggregation, which is represented by A. It can be expressed as $A \in R^{I_p \times I_s \times I_{ts}}$, where I_p represents the physiological characteristic; I_s is the affective state analyzed from social network data; and I_{ts} represents the time-space.

As shown in Fig. 5, each matrix describes a user's physiological characteristics at a certain time-space label. A matrix is created for each class of affective state based on the recognized emotions of a social network. The elements in each matrix show the weight of a user's emotion in a given place and time. In summary, the core of emotion-driven multidimensional data aggregation and preprocessing is big emotional data aggregation characterized by "one key value and two categories of data processing in CPS-Spaces."

Model Evolution — Analysis and prediction results are verified using social network data, which further enhance the accuracy of theexisting model. Since an individual's social network data is collected with a certain time-space label, we are able to verify the results of sentiment analysis and prediction based on physiological characteristics with the same time-space label according to the affective state identified based on texts and facial expressions. In addition, data with the time-space label can be updated to the existing tensor model to enhance its accuracy.

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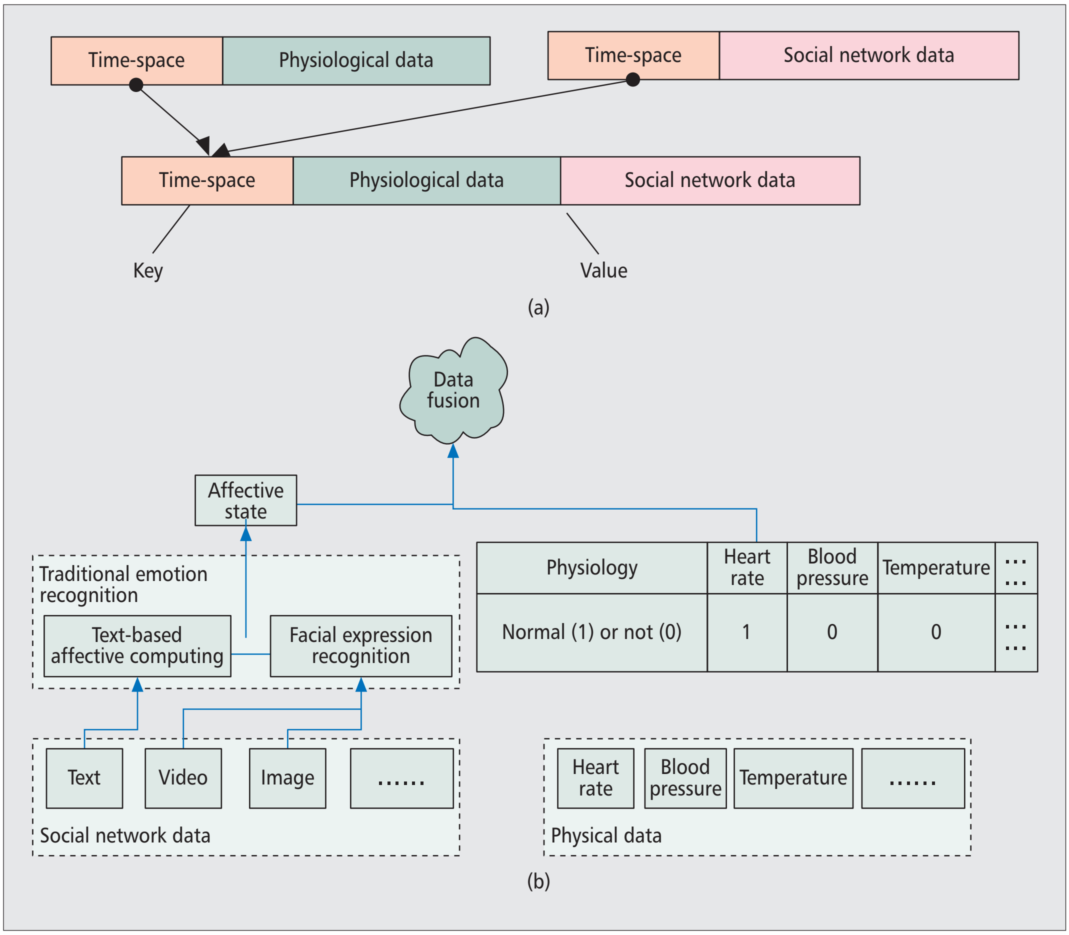

Figure 4. Structure and fusion of multidimensional data: a) data structure with time-space label as the key; and b) various emotional data fusion.

An AIWAC Testbed for Emotion-Aware Applications Based on Robot Technology

In this section, as an illustration, we briefly introduce an affective robot testbed developed by the Embedded and Pervasive Computing (EPIC) Laboratory at Huazhong University of Technology and Science, which aims to provide the home user with emotion-aware services.

Testbed Architecture

As shown in Fig. 6a, the testbed consists of a robot, a smart access point (AP), and a data center (DC). The detailed mechanism is described as follows:

- Sensory data, including physiological and psychological data, are transmitted from robot to smart AP. These data are not only sensed by wearable devices on users, but also the sensors on the robot, such as camera and microphone.
- At the smart AP, sensory data are cleaned and compressed in order to enhance the network performance and reduce DC workload.
- The preprocessed data are analyzed via affective computing in the DC. According to the results of analysis, an affective feedback solution is generated with a series of commands sent to the smart AP. More details will be introduced in the next subsection.
- Once the robot receives the command queue from the smart AP, it takes emotion-aware actions through executing commands in the queue, as shown on the lower left of Fig. 1.

Technical Details

The testbed provides two versions of software available to run in Windows and Linux in the DC, which can generate command queues according to analyzed results. Figure 6b illustrates the software interface running on Windows, while Fig. 6c illustrates the Linux version. In contrast, the software in the robot is only available on Android, as shown in Fig. 6a. Figures 6b and 6c include five types of commands sent to the robot:

- Moving forward
- Changing moving direction
- Turning on/off LED
- Rotating head
- Stopping all actions

These commands are transmitted from the DC to the robot via TCP. With more devices placed on on the robot or surrounding devices recognized by the robot, the testbed will support more actions.

Open Issues and Future Directions

In order to enhance QoE for affective interaction, we utilize a media cloud platform to store, manage, and analyze emotional data to provide timely emotion interactive services. Since mobile

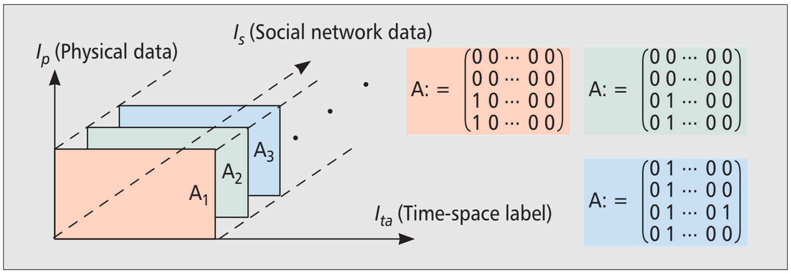

Figure 5. Tensor-based multidimensional emotional data aggregation model.

cloud computing allows users to maintain maximum freedom in time and space, we employ it to overcome the shortcomings of poor timeliness and space constraints in traditional emotional interaction. Results of sentiment analysis are fed back to the user for emotional interaction with the user by perceiving any available multimedia devices around the user. When emotional interaction is temporarily interrupted or the user environment changes, the resources in the new environment need to be quickly perceived, allocated, and optimized to continue the interaction in order to provide users with high QoE of emotion interactive services. Thus, we need to efficiently manage the network resources and elaborately design the data processing method.

• Emotion-driven available resources perception and allocation: Since a user's emotions are affected by many factors, the data should be collected as broadly as possible by wearable devices in order to make a timely and accurate judgment. Furthermore, it is challenging to evaluate which kind of data is useful for sentiment analysis. First, the emotional perception models should be established based on the factors affecting a user's emotions. Then, based on the models, we can decide the active duration of the wearable devices to collect essential data.

• Theory and method of dynamic controllable emotional interaction: A user's physical location usually dynamically changes, but carriers (PC, mobile device, home appliance, robot, etc.) and media (image, audio, lighting, etc.) used for emotional interaction are relatively static. Therefore, how to control the dynamic and real-time emotional interaction according to a user's location changes is another open issue.

• Intelligence reinforcement theory and method based on an upright walking robot: For humanized and intelligent feedback, emotional interaction should have affinity. With the accurate analysis and prediction of a user's emotions, a variety of humanized ways for emotional interaction will directly affect the user's experience. We intend to build an intelligent upright-walking robot by integrating interdisciplinary study results in many fields. With high biofidelity, the robot carries multiple sensors that can collaborately work together with other smart devices to sense environmental information. The robot will become one of the most intimate, emotionally dependable front-end carriers for emotional interaction with people. Meanwhile, relying on wireless communication and cloud computing technology, the intelligence of the robot is largely enhanced when it is moving through various actions. Thus, intelligent reinforcement theory and corresponding approaches are desired for effective interaction, which is another open and challenging issue for the community.

Conclusion

In this article, we have designed a novel affective interaction architecture named AIWAC, which aims to provide users with emotion-aware services. According to the requirements of sentiment analysis, we have proposed an approach based on wearable computing for emotional data acquisition to ensure data sufficiency. Furthermore, we have proposed a cloud-based approach to achieve a twofold goal:
- Hybrid emotional data analysis, which supports computation-intensive analysis of various emotional data from CPS-Spaces
- Dynamic resource perception and allocation, which provides users with real-time, available, and effective affective interaction

Finally, an AIWAC testbed for emotion-aware application based on a robot has been presented. Based on this architecture-level design, we will investigate how to provide mobile users with resource-intensive and emotion-aware services while achieving a flexibile trade-off between communication and computation as future work.

References

[1] S. Cotton, A. Meijerink, and W. Scanlon, "A Glove-Based Gesture Interface for Wearable Computing Applications," *Proc. IEEE PIMRC '13*, London, U.K., 2013, pp. 58–62.
[2] S. Hamida *et al.*, "Towards Efficient and Secure In-Home Wearable Insomnia Monitoring and Diagnosis System," *Proc. IEEE BIBE '13*, Chania, Greece, 2013, pp. 1–6.
[3] T. Taleb, D. Bottazzi, and N. Nasser, "Novel Middleware Solution to Improve Ubiquitous Healthcare Systems Aided by Affective Information," *IEEE Trans. Info. Tech. in Biomedicine*, vol. 14, no. 2, 2010 , pp. 335–49.
[4] H. Wang *et al.*,"Resource-Aware Secure ECG Healthcare Monitoring through Body Sensor Networks," *IEEE Wireless Commun.*, vol. 17, no. 1, Feb. 2010, pp. 12–19.
[5] Y. Zhang *et al.*, "Home M2M Networks: Architectures, Standards, and QoS Improvement," *IEEE Commun. Mag.*, vol. 49, no. 4, Apr. 2011, pp. 44–52.
[6] X. Wang *et al.*, "Cache In The Air: Enabling the Green Multimedia Caching and Delivery for the 5G Network," *IEEE Commun. Mag.*, vol. 52, no. 2, Feb. 2014.
[7] X. Ge *et al.*, "5G Wireless Backhaul Networks: Challenges and Research Advances," *IEEE Network*, vol. 28, no. 6, Nov. 2014, pp. 6–11.
[8] M. Chen, S. Mao, and Y. Liu, "Big Data: A Survey," *ACM/Springer Mobile Networks and Applications*, vol. 19, no. 2, Apr. 2014 pp. 171–209.
[9] M. Chen, Y. Wen, H. Jin, V. Leung, "Enabling Technologies for Future Data Center Networking: A Primer," *IEEE Network*, vol. 27, no. 4, July 2013, pp. 8–15.
[10] T. Taleb, "Towards Carrier Cloud: Potential, Challenges, and Solutions," *IEEE Wireless Commun.*, vol. 21, no. 3, June 2014, pp. 80–91.

Biographies

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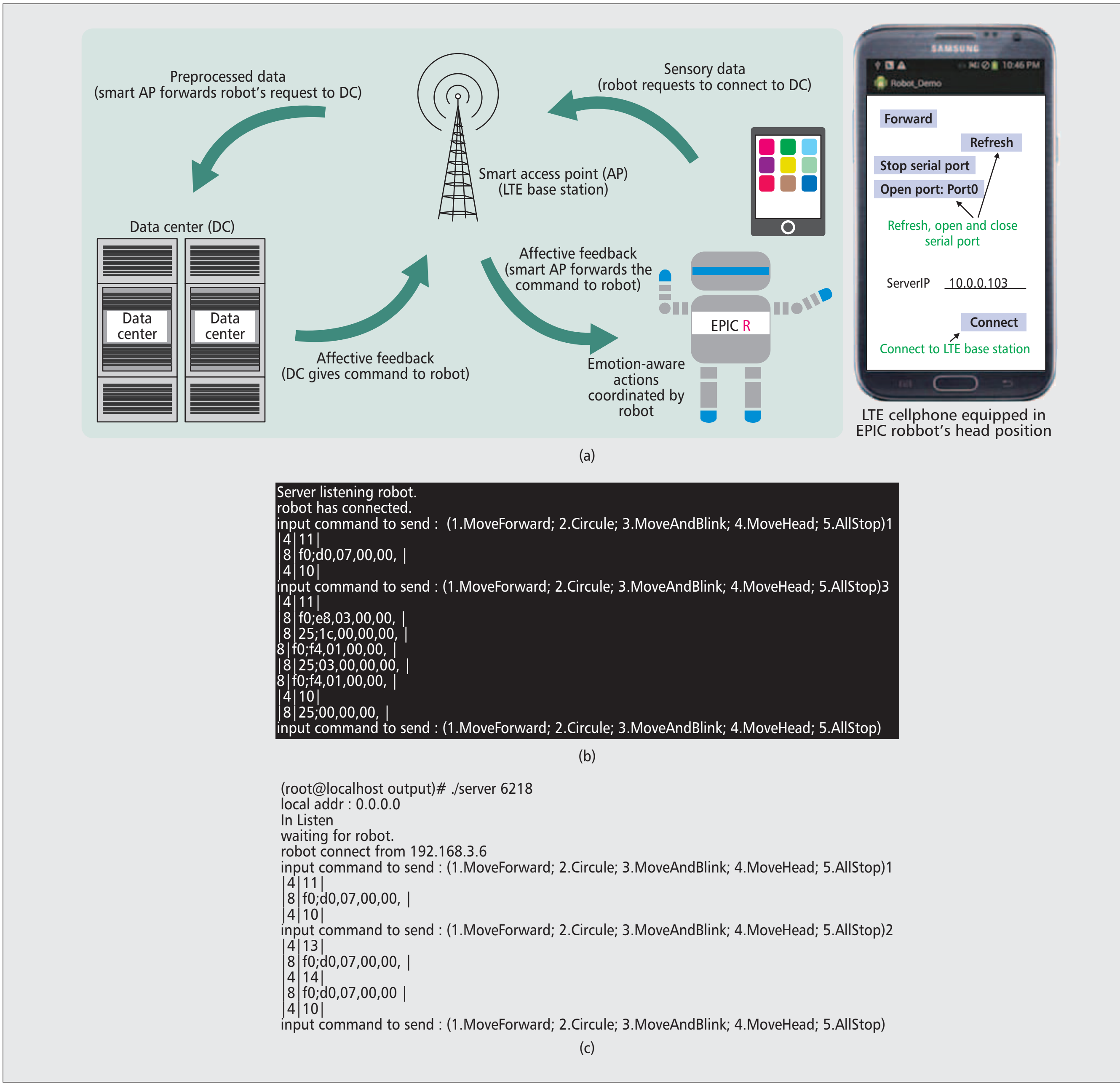

Figure 6. AIWAC testbed architecture and software interfaces: a) AIWAC testbed architecture; b) software interface in Windows; c) software interface in Linux.

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