SPHA: Smart Personal Health Advisor Based on Deep Analytics

Min Chen, Yin Zhang, Meikang Qiu, Nadra Guizani, and Yixue Hao

It is crucial to monitor and avoid users' unhealthy behaviors. Existing health monitoring approaches still face many challenges of limited intelligence due to insufficient healthcare data. Therefore, this article proposes a smart personal health advisor (SPHA) for comprehensive and intelligent health monitoring and guidance.

Abstract

According to a report by the World Health Organization, diseases caused by an unhealthy lifestyle represent the leading cause of death all over the world. Therefore, it is crucial to monitor and avoid users' unhealthy behaviors. Existing health monitoring approaches still face many challenges of limited intelligence due to insufficient healthcare data. Therefore, this article proposes a smart personal health advisor (SPHA) for comprehensive and intelligent health monitoring and guidance. The SPHA monitors both physiological and psychological states of the user. The SPHA-Score model is proposed to evaluate the overall health status of the user. Finally, a testbed for verification of feasibility and applicability of the proposed system was developed. The experimental and simulation results have shown that the proposed approach is efficient for proper user state monitoring.

Introduction

The World Health Organization (WHO) reported that the noncommunicable diseases caused by unhealthy lifestyles cause a large number of deaths all over the world. Among these deaths, more than 40 percent are related to people under the age of 70 years old [1]. To address this urgent health issue, WHO proposes an explicit roadmap to "slow the public health disaster," which is devoted to effective avoidance of unhealthy lifestyles, including smoking, alcoholism, lack of exercise, excessive salt intake, and so on. To achieve lifestyle changes, it is crucial to monitor unhealthy living behaviors and habits. Thus, the design of efficient health monitoring has become a hot research topic in recent years. Generally, out-of-hospital monitoring conducted by users themselves is widely used due to cost effectiveness, convenience, and flexibility [2]. The deployment of such a self-monitoring system corresponds to a typical diagnosis mechanism based on physiological data to evaluate the user's health status. The limited data of one-dimensional body signals through current commercialized wearable devices (e.g., smart watch and bracelet) can hardly lead to an informative health advisor. Specifically, users often feel uncomfortable during hospital-based data acquisition through a medical wearable device, which reduces their interest in participating in long-term monitoring [3]. Therefore, more comfortable and accurate monitoring should be developed to ensure sustainable health data acquisition.

With the development of communication and sensing technologies[4], various body sensors have been deployed to monitor users' health status and behaviors [5]. These monitoring systems for physiological and psychological behaviors mainly consist of two components: an embedded sensing device for transforming body signals into digital signals, and a data processing module for body signal collection, storage and processing. In recent years, various healthcare applications for physiological monitoring have been developed, such as physical condition warning [6] and chronic disease detection [7]. Although psychological monitoring technologies are immature, there have been some novel applications to analyze a user's emotional status by wearable devices [8]. For instance, Wearable 2.0 can record an electrocardio signal and infer a user's emotion [9].

However, existing approaches based on psychological data analytics usually exhibit deficiency in terms of data sharing and reuse due to the privacy of a user's mental status. For instance, Gaggioli *et al.* [10] developed a platform to collect psychology, physiology, and activity information for providing psychological services. However, these systems have the following shortcomings.

Elementary Function: Only physiological or psychological information is considered, but this information is insufficient to fully monitor the user's long-term status. According to Maslow's theory of needs, human motivations generally move through the phases "physiological," "safety," "belonging and love," "esteem," and "self-actualization" [11]. However, existing systems only focus on the lower motivations (e.g., physiological and safety). Thus, higher-level motivations, such as approval from others and contributions to society, should be considered in advanced systems.

Limited Intelligence: Only simple services are supported, such as monitoring and warning. A comprehensive system is expected to provide intelligent healthy guidance, which should consist of a brain-like learning model for the cognition of a user's spiritual states with recognition regarding the pattern of user behavior.

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In order to address these issues, a more comprehensive monitoring system based on multi-dimensional health data should be developed. Thus, we propose a smart personal health advisor (SPHA) to provide comprehensive and intelligent health monitoring and guidance. The SPHA is able to monitor both physiological and psychological states of a user and it is expected to evaluate the user's overall status by the SPHA-Score model, where SPHA-Score has the following meanings:

- Denotes leading of a healthy and good life style by monitoring a user's physiological and psychological data
- Represents a user's self-value and social impact
- Helps a user to be more successful by improving his/her ability

Specifically, the main contributions of this article include enabling context awareness sensing to collect heterogeneous information, providing context analysis to obtain the user's physiological and psychological status by deep learning, and developing context reasoning to help the user realize self-worth and social value.

The article is organized as follows. In the following section, we present the details of the SPHA system, including architecture and application scenarios. The SPHA-Score model is then introduced, and the testbed is given following that. Finally, we conclude the article.

SPHA Architecture

The SPHA architecture provides the technical convenience that benefits the user. Relying on the big data with the fusion of historical and immediate healthcare data, the system supports learning-based cognitive wisdom, which is used as a reference for the user and to further promote his/her self-awareness. The SPHA gains the reinforcement learning ability by continuous learning from historical big data. Meanwhile, the SPHA gradually understands the user during the interactive process, and further provides a more efficient and interactive interface to the user.

Based on the learning and analysis of the combined historical data and a user's personal data, the intelligence of understanding the user in the SPHA is strengthened. Namely, the main goal is to provide a personalized life guidance to the user. Furthermore, the SPHA participates in the user's daily activities, interacting with the surroundings, and accordingly guides the user as a tutor. Meanwhile, the SPHA carries out continuous learning from the user's daily activities and promotes cognitive wisdom by comprehensive utilization of activity data from multiple users.

Above all, the SPHA attempts to build an association among social science, philosophy, and recent technology advances in terms of communication, computing, and networking. The SPHA realizes the ultimate humane concern through scientific and technological means, while taking into account how comfortable the user is in terms of the physiology and psychology. Moreover, the SPHA is designed to provide the SPHA-Score to users. The SPHA-Score depends on both self-value and social value, wherein the value is composed of both material wealth and spiritual wealth. The self-value represents the user satisfaction with material and spiritual wealth, and can be judged by the user's health status and mood states. The social value can be assessed by a domain expert based on the user's behavior.

The overall architecture of the SPHA is shown in Fig. 1. Every user possesses an individual SPHA-Score. Every "flower" stands for one user having his/her own SPHA-Score system. There are four levels in the SPHA. The first level is "soil" for the "flower" to grow, the second level is "leaves," the third level is "petals," and the fourth level is "stamen and pistil." To be more specific, "soil" consists of the user's personalized data in terms of body signals, emotion states, environmental parameters, and so on. The data is collected by various networking and communication infrastructures, including fifth generation (5G) networks, cognitive systems, the Internet of Things (IoT), body area networks, robotics, and so on. The "leaves" level includes three components: data classification (i.e., the classification on statistics data, time series data, and text data), data preprocessing, which includes data reduction, data transformation, and data cleaning, and data analysis, based on machine learning, deep learning, and cognitive computing. The "petal" level reflects the results of physiological or psychological analysis of the user, which includes emotion detection, behavior analysis, fatigue detection, physiological status monitoring, emotional care, potential disease analysis, social impact analysis, cognitive context analysis, and so on. The "stamen and pistil" level represents the objective of the SPHA-Score system.

Generally, the SPHA framework can be divided into three parts.

Low-Level Context Awareness: The information collected by IoT sensors is multi-dimensional data. In essence, the environmental information is the comprehensive depiction of multi-domain and multi-modal heterogeneous information. Specifically, the collected information includes timestamp, location, physiological data, active status, social media data, and environmental data.

Middle-Level Context Analysis: The second level is intended for data analysis. First, the raw data is unstructured, redundant, and inconsistent, so it is necessary to carry out preprocessing, which includes data cleaning, formatting, and standardization. Then these data is uniformly expressed by the tensor, involving the structured and unstructured data from the physical world, cyberspace, and the user's social network, which can be represented as $A \in R^{I_t \times I_x \times I_y \times I_z \times I_r \times I_u}$, where $I_t I_x I_y I_z I_r I_u$ represents the time, physical word (X, Y, Z), cyberspace, and user's social network, respectively. $I_t \times I_x \times I_y \times I_z \times I_r \times I_u$ represents the Cartesian product of six dimensions. The sixth order tensor can be seen as a six-dimensional matrix, and each dimensional matrix is seen as a mode expansion matrix of the tensor.

High-Level Context Reasoning: At this level, data processing based on deep reinforcement learning is performed. Using the location information combined with the usage pattern of a mobile phone, we can infer a user's activity. For instance, the user may be studying when he/she is in a laboratory, or he/she may be driving when he/she is on an expressway. Using physiological information, we can judge the physical conditions and mental state of the user. The individual value of

The SPHA architecture provides the technical convenience that benefits the user. Relying on the big data with the fusion of historical and immediate healthcare data, the system possesses the potential to achieve a learning-based cognitive wisdom, which is used as a reference for the user, and further promote his/her self-awareness.

It is often said that material is the foundation of the spiritual level. For the majority of people, physical health is the basis of psychological health. Only when good health conditions are possessed, the psychological and spiritual level can be pursued (excluding some patients with an optimistic mood). Thus, we cannot treat the physical health and psychological health equally.

the user is initially evaluated by the user at intervals. On the other hand, the social value is evaluated by experts, and the stability of the social value is greater than that of the individual value. The SPHA-Score is the weighted sum of the individual value and the social value.

In addition, the features extracted by deep learning are often more valid than artificial features. Therefore, the evaluation standard is determined by deep learning, wherein the input is the multidimensional multi-modal data collected by sensors, and the output is the score after training. Due to the dynamic evaluation standard, reinforcement learning is adopted to find out the strategy that makes the cumulative reward maximal. The real-time data are obtained constantly, and the behavior is accordingly suggested to the user. When the user responds, a new behavior will be suggested consequently. Thus, the SPHA-Score maximum is calculated in combination with other data.

The SPHA-Score has many applications. For example, as shown in Fig. 2, Rachel and Bob are two lovers, and they have a date at a cafe. Both Rachel and Bob have a SPHA-Score of her/his own. Each one's SPHA would be influenced by various aspects, including his or her parents, pet, geographical factors, and so on. From the figure, we can see that Bob's SPHA suggested having a date in this cafe according to a few factors includ-

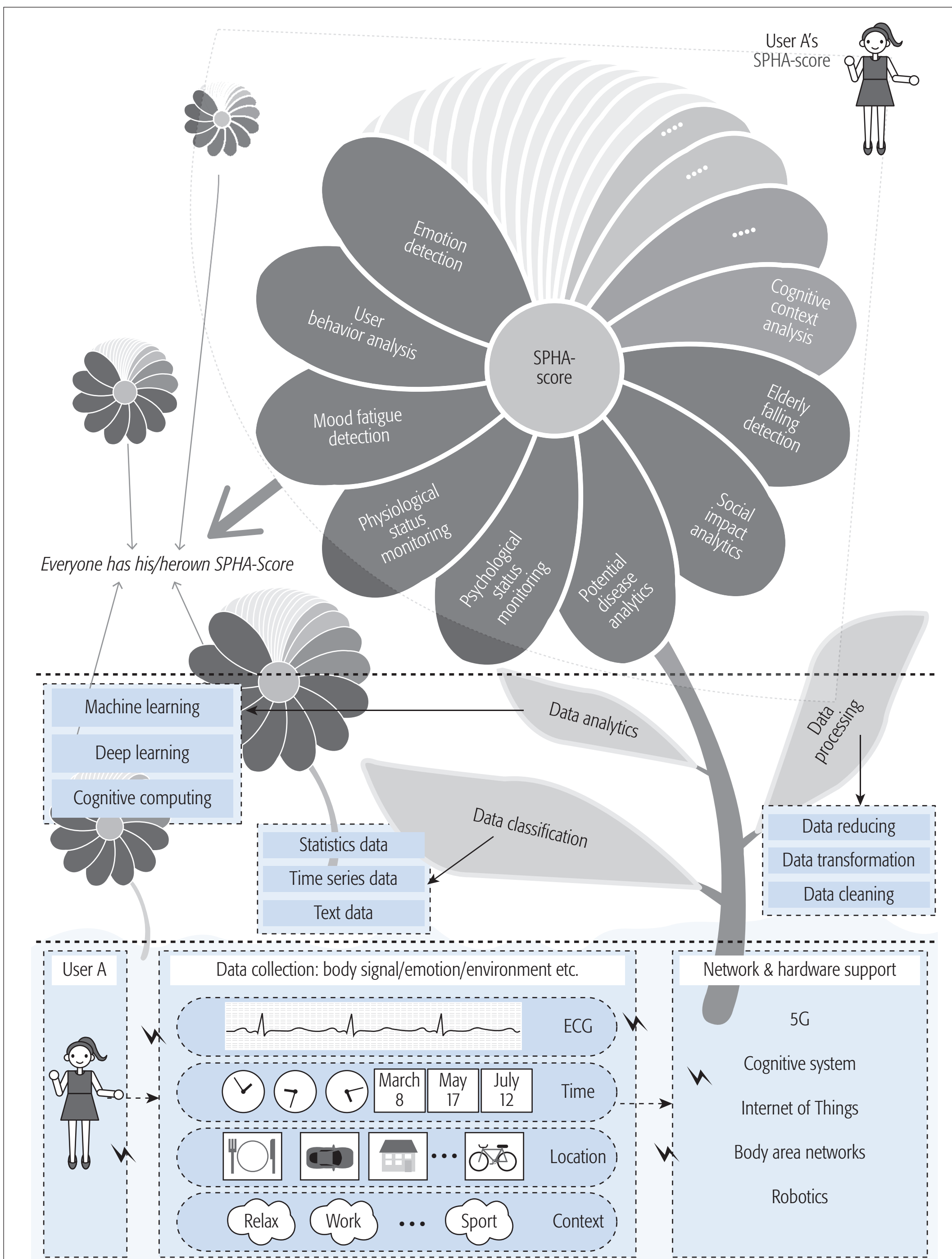

Figure 1. Illustration of the SPHA architecture.

ing past experience with Rachel, family addresses of the two parties, and so on. Bob adopted this suggestion. After Rachel received the invitation, she agreed joyfully. When she was bothered about what to wear, her SPHA would give advice. With his SPHA's suggestion, Bob arrived at this cafe five minutes earlier, and he chose a table by the window that Rachel likes. When the two lovers order food, the SPHA suggested that the cheese mousse is very particular and that Rachel might like it, and classic mocha is recommended for Bob. Later, it is suggested by the SPHAs, according to their states, that they should go to the cinema or Bob should send Rachel back home. After this date, the favor degree of thm increases, while their SPHA-Scores are improved.

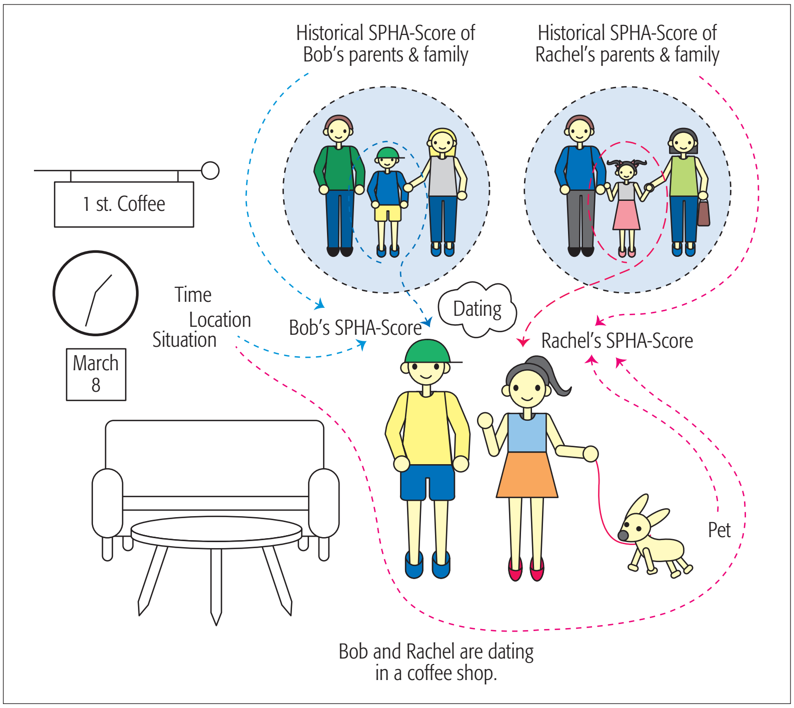

Figure 2. SPHA scenarios.

SPHA-Score Model

In this section, we introduce the SPHA-Score model, as shown in Fig. 3. The SPHA-Score mainly focuses on health status, self-worth, and social value.

Health Status

The user's health status is evaluated according to his/her physiological and psychological status.

Physiological status is often analyzed from heartbeat, body temperature, blood pressure, and so on, which are mainly based on feature learning from the following three categories of physiological data: structured data, which is often similar to the medical record to store the user's basic health information, and the features can be extracted by principal component analysis (PCA) or factorization [12]; text data, which are mainly diagnoses from doctors, and the convolutional neural network (CNN) is an effective approach for feature learning from the text data [13]; and image and video data, which are often generated by medical devices, such as electrocardiogram, computed tomography, and B-scan ultrasonography, and CNN is also suitable to extract features from the data [14]. These features are deemed the input of a classifier, and the SPHA-Score of someone's physiological status is output.

Psychological status cannot be directly collected, but it can be recognized from the psychological signal, mobile data, facial expression, voice, and so on. Specifically, using temporal Bayesian fusion [15], the data can be fused, and then the user's psychological feature can be extracted while the status can be recognized.

Personal Value

The SPHA-Score reflects the trail of various long-term and integrated factors, and is also an embodiment of a user's personal values within a certain period of time. The size of this period of time is called the "time window," and here it is represented by T. Thus, an SPHA-Score is not a time-related continuous function. However, personal physical health or psychological health is a time-related continuous function that f_{body} and $f_{emotion}$ are the continuous differentiable functions related to time t. For example, at a moment t_0, the physical health and psychological health have unique numerical values. Therefore, the integral of f_{body} and $f_{emotion}$ within the time window can be expressed as the physical and psychological health of the user. The personal physical health S^T_{body} and psychological health $S^T_{emotion}$ within time window T can be calculated as $S^T_{body} = (1/T) \int f_{body}dt$ and $S^T_{emotion} = (1/T)\int f_{emotion}dt$.

It is often said that material is the foundation of the spiritual level. For the majority of people, physical health is the basis of psychological health. Only when good health conditions are possessed cab the psychological and spiritual levels be pursued (excluding some patients with optimistic outlooks). Thus, we cannot treat the physical health and psychological health equally and a nonlinear combination model should be considered.

Social Value

The social value of a person relates to his/her responsibility and contribution to society. Namely, different domains have different recognition standards. For instance, the application of some technical invention in the computer domain becomes instantly known worldwide, while breakthroughs in domains such as archaeology and language are rarely widely known, although they make great contributions in their own fields. Therefore, we should discuss the social value of an individual in view of different domains.

Obviously, we would rather say that someone has accomplished something remarkable during a certain period of time than that he/she made a great contribution to society in that period. Hence, the social value is difficult to evaluate. For instance, the number of articles that researchers had published within a year, the quality of these articles, the number of meetings and scientific research exchange activities the researchers participated in, their earnings, the number of students they attracted, the earnings of those students during that period: all of this data can be used to measure the contribution of researchers in the scientific field.

Suppose that the index of a social contribution of an individual in a domain G is determined as

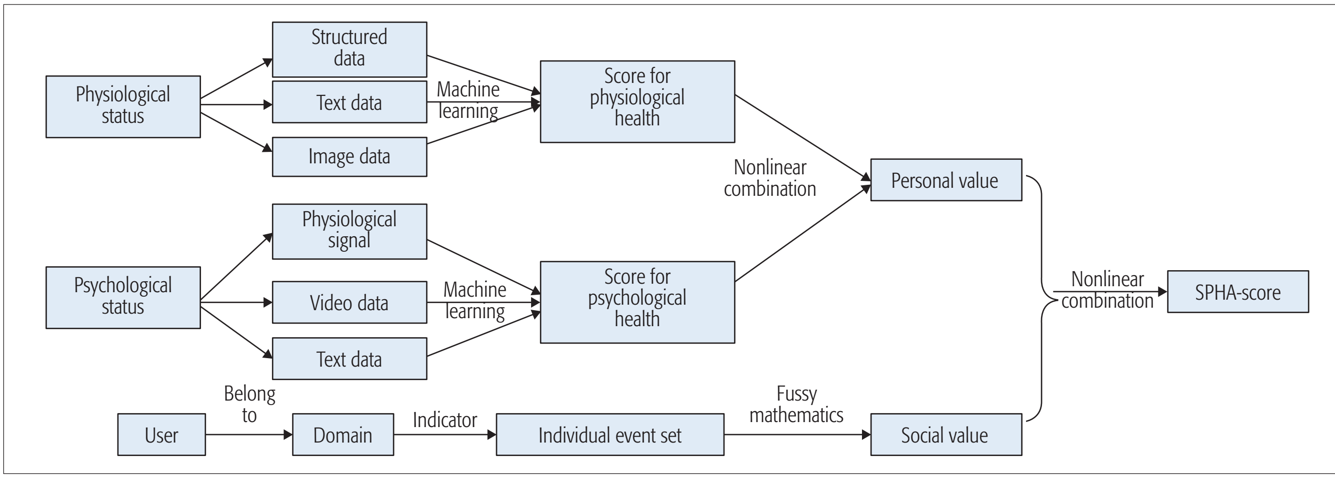

Figure 3. Illustration of the SPHA-Score model.

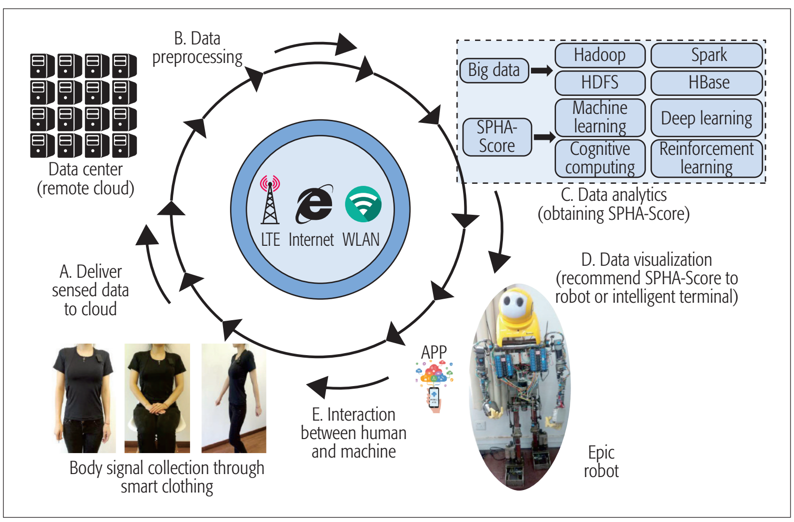

Figure 4. SPHA testbed.

follows. The m indexes are determined jointly by some experts in this domain. A person P_0 makes a more or less positive or negative contribution in this domain under various indices (e.g., crime is a negative contribution). Therefore, $P_0|Q_1 = \{q_1, q_2, \cdots, q_l\}$ represents his/her contribution in this domain, where $q_i (i = 1, 2, \cdots, l)$ indicates the specific event under the index of $Q_i (i = 1, 2, \cdots, m)$. For instance, Q_1 indicates the index of article publishing in a scientific research field, and q_i indicates some specific article, while $P_0|Q_1$ is the collection of all articles published by that individual within a time window T. Thus, the social contribution of an individual within time window T in domain G is defined by: $C^G_{p0} = P_0|Q = \{P_0|Q_1; P_0|Q_2; \ldots ; P_0|Q_m\}$.

Furthermore, the contribution of all individuals $P = \{P_1, P_2, \ldots , P_s\}$ within a time window T in domain G can constitute the contribution matrix C^G_P. Although the events do not have comparability under different indexes Q_i, different individual event sets under the same index are comparable. For instance, the social contribution of a science researcher A under index Q_1 (article published) is $\{t_1{:}2.231, t_2{:}1.245\}$ (the value shows the influence of the article). The social contribution of another science researcher B under index Q_1 is $\{t_1{:}4.251, t_2{:}5.125, t_3{:}2.712\}$. According to the article index, researcher B makes a greater social contribution than researcher A. Therefore, we can build the optimal social contribution $P^*|Q$ within a certain domain. Applying the knowledge of fuzzy data, we can map the social contribution $P^*|Q$ in domain G within the interval [0,1]. Thus, the lattice approximate degrees of $u_{P_i|Q_j}$ and $u_{P^*|Q_j}$ are determined by the lattice approximate degree method, and then the social value of the individual in domain G can be determined.

The SPHA Testbed

In this section, we illustrate a testbed of the SPHA system, which is shown in Fig. 4. There are three main components of this testbed: EPIC smart clothing, EPIC robot, and data center. The sensors for collecting the user physiological information are arranged properly into smart clothing equipped with a flexible cable. The EPIC robot is humanoid in order to motivate the user to interact with it, while it collects information on the user state during the interactions. Bluetooth is used for short-range communication, and LTE or WiFi is used for remote communications. Specifically, we collect two different kinds of user data as the data source for analysis.

Physiological Data Based on Smart Clothing: When the user is in an indoor or outdoor environment, the smart clothing that the user wears can collect the physiological data of the user, such as electrocardiograph, temperature, and blood oxygen. The data is uploaded to the data center for analysis.

User Behavioral Data Obtained by Interaction with EPIC-Robot: If the user is in a closed indoor environment, while interacting with the user, the EPIC robot continually collects information about the user, such as facial expression, which is sent to the data center for analysis through LTE or WiFi.

In this article, we use the corporation Insupr's big data solution to construct our data center, which consists of two management nodes and seven data nodes, and the Hadoop 2.0 solution is deployed in the data center. Based on the SPHA-Score model, we can obtain the SPHA-Score in the data center. Then the data center recommends the SPHA-Score to the EPIC robot or intelligent terminal, and the EPIC robot interacts with the human.

On the basis of the presented infrastructure, we evaluated the interactive end-to-end delay, which included uplink delay (i.e., time delay of delivering sensed data to the cloud), analysis delay (i.e., time delay of data processing and analytics), downlink delay (i.e., time delay of feeding back the SPHA-Score to the EPIC robot), and action delay (i.e., time delay for the EPIC robot doing an action). As shown in Fig. 5, six tests were performed in order to determine the interactive end-to-end delay. From the figure, we can conclude that the uplink delay, analysis delay, downlink delay, and action delay are about 300 ms, 150 ms, 25 ms, and 100 ms, In the future, we expect to extend this system to give users' personal values and social values in order to obtain the users' SPHA-Scores.

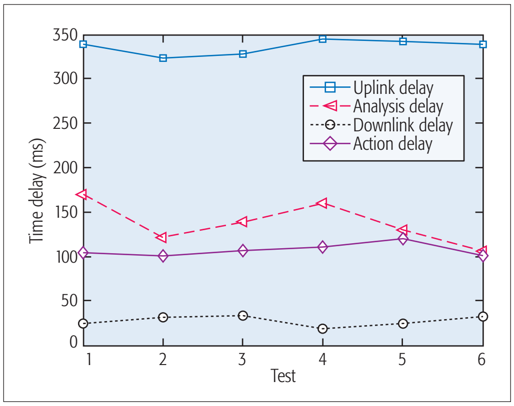

Figure 5. Evaluation of interactive end-to-end delay.

Conclusion

Nowadays, the monitoring of unhealthy behavior is attracting extensive attention, but most of the existing approaches have practical limitations and do not consider the user's high-level spiritual needs. In order to solve the aforementioned problems and to provide a more universal model, this article proposes a novel deep-level health monitoring and guiding system, the SPHA, which is able to realize cognition of users' personal values and social values in order to guide them to have healthier lifestyles. Moreover, the proposed system was verified by the SPHA testbed, which was developed to collect three categories of data and realize three-level cognition, for example, physiological and psychological status, personal value, and social value. The results have shown that the SPHA provides successful and intelligent health monitoring and guidance.

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