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SCAI-SVSC: Smart clothing for effective interaction with a sustainable vital sign collection

Long Hu [a], Jun Yang [a], Min Chen [a], Yongfeng Qian [a,*], Joel J.P.C. Rodrigues [b,c,d,e]

[a] School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan 430074, China
[b] National Institute of Telecommunications (Inatel), Brazil
[c] Instituto de Telecomunicações, Portugal
[d] ITMO University, St. Petersburg, Russia
[e] University of Fortaleza (UNIFOR), Brazil

HIGHLIGHTS

- Develop smart clothing to collect human body physical signs.
- Design the data transmission and communications of smart clothing.
- Realize automatic emotional interaction by monitoring the ECG signals.

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ABSTRACT

In this paper, we propose a new wearable device named smart clothing. Compared with traditional equipments smart clothing has lots of advantages in many aspects. This paper introduces the construction of smart clothing system, discusses its usage scenario and the data transmission mode with the terminal, cloud platform, and builds an efficient healthcare system. This paper also discusses the use of smart clothing for measurement of human body signs such as blood oxygen, body temperature, heartbeat, and ensures users being in good health by real-time monitoring. Finally, this paper focuses on the collection of ECG signals and the experiment of analyzing user's feelings.

1. Introduction

1.1. Background and preliminaries

Chronic disease has become a worldwide problem. Since 2000, the World Health Organization (WHO) has made considerable efforts to improve chronic disease prevention and control. WHO has also helped to establish partnerships and networking among its member states, to encourage the development of policies, networks, and programs, aiming at preventing and controlling chronic diseases [1,2]. However, these strategies are not easily widely implemented. Furthermore, due to the increasing cost of healthcare and the aging population, there is a developing need to monitor patients' health status in non-clinical environments. It thus requires significant efforts to address the challenges to solve a series of healthcare problems for an aging population, patients of chronic diseases, patients in a rehabilitation period, and sub-healthy people [3]. To this end, functions such as sustainable physiological indicators monitoring, disease management, and remote medical services are in great demand [4]. The specific methods include the following.

- *Medical facility based services*. Healthcare systems are deployed in medical and health institutions or nursing institutions, where health indicators for elderly people are automatically monitored. This part of workload on doctors and nurses could usually be heavy.
- *Personalized health services*. It is not enough that a monitoring system work only for disease prevention and risk prediction for patients with chronic diseases. Customized healthcare services are also very helpful, especially for rehabilitation care and medical care when users are mobile. Their goal is to provide physiological data acquisition, health analysis, and continuous consultation anytime and anywhere. This healthcare service effectively guides sub-healthy people to

* Corresponding author.
E-mail address: yongfengqian@ieee.org (Y. Qian).

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change their lifestyle, control risk factors, promote physical exercises, and even realizing self health management nowadays.

- *Rehabilitative medical auxiliary*. Rehabilitative medical auxiliary can shorten the time patients need for rehabilitation and shift traditional rehabilitation from hospitals to household rehabilitation monitoring. Thus, the financial burden of patients can be alleviated, and the turnover rate of sickbeds in hospitals can be improved. The profit model of hospitals can also be upgraded.

To satisfy such new demands, a variety of system prototypes and new products have been introduced in recent years. They all aim at providing real-time information about one's health condition [5]. To collect real-time information, providers are focusing on wearable systems. The wearable systems for health monitoring may comprise various types of minimum sensors, most of which are wearable or even implantable. These sensors can measure detailed physiological indicators such as heart rate, blood pressure, body and skin temperature, oxygen saturation, electrocardiogram, etc. However, these devices can be too expensive or not convenient enough; for example, see LiveNet [6] by The Media Laboratory of MIT. By comparison, with a flexible distributed mobile platform, long-term health monitoring applications have been proposed, along with real-time data processing and streaming, and context classification. Such existing products include MagIC [7] and LifeGuard [8].

Although these existing products or prototype systems provide good solutions to the above mentioned series of health problems, many open problems and challenges remain to be addressed. In this paper, we propose to provide smart clothing, based on the new wearable computing technology for healthcare [9]. Some typical applications of smart clothing are described below.

1.2. Typical applications of smart clothing

1.2.1. Applications of healthcare for elderly people

Elderly people often suffer from a variety of chronic diseases, such as cardiovascular and cerebrovascular diseases, hypertension, and diabetes. Furthermore, their ability to take care of themselves is usually limited. Therefor, a healthcare system for elderly people should be comfortable and convenient to use. A healthcare system based on smart clothing can achieve real-time healthcare, and doctors can then apply appropriate medications for common diseases of the elderly when needed.

1.2.2. Community-based medical and healthcare services

The shortage of medical and health resources is a worldwide challenge. The application of smart clothing in medical and health institutions could help to meet this challenge. Traditionally, measurement of some common vital signs of patients is conducted manually by doctors and nurses. This will be transformed to automatic measurement based on physical signs collected by smart clothing. Thus, the cost of manpower will be greatly reduced. In addition, the sustainable monitoring capability of smart clothing helps to guide doctors in terms of disease diagnosis, medication usage, and rehabilitation planing. It will greatly enhance the level of medical service in hospitals.

1.2.3. Smart fitness and training for athlete and sportsman

High-speed running and collisions are a severe test for physical signal collection. In addition, there is a need to detect parameters like sharp turning, sharp stop bouncing, and so on, which require smart clothing to be equipped with more sensors. Furthermore, players run at a larger scale on the playing field. It is most necessary to transmit real-time data to the cloud platform through wireless communications. This kind of real-time detection, transmission, and evaluation can strengthen the value of players' training sessions. After training, players can recall the training scene and analyze their performance. The general effectiveness is far from real-time guidance. Therefore further research is needed on long-distance and multi-point transmission technology based on low power consumption Bluetooth or low power consumption WiFi.

1.3. Our contributions

In this paper, we present a new kind of smart clothing equipment which is different from traditional wearable devices, and realize the real-time emotion detection based on the smart clothing. Our contributions in this paper can be summarized as follows.

- Enable real-time collection of human body physical signs by the smart clothing equipment.
- Complete the data transmission and communication of smart clothing equipment with terminal and cloud platform.
- Realize the user's emotional interaction by means of monitoring the ECG signals.

The reminder of this paper is organized as follows. We review related work in Section 2. In Section 3, we present the architecture for sustainable vital sign collection through smart clothing. In Section 4, we examine using smart clothing for affective interaction. The testbed implementation and experimental study are presented in Section 5 and Section 6 concludes this paper.

2. Related work

2.1. Electronic fabrics for wearable computing

In recent years, the appearance of textiles, electronic fabrics, and wearable electronic products have achieved a high charge of integration. The development of wearable medical instruments has entered into a new stage. Electronic textile instruments with fibrous structures, such as fabric sensors, drivers, circuits and electrodes, are produced by the use of various conductive materials, semiconductors, and insulation materials. These items have almost the same appearance as ordinary clothing after their integration. The flexible electronic fabrics with electrical properties can be attached to the bodies of examinees comfortably for a long period of time for continuous monitoring. Collection and transmission of basic physiological signals of the human body can be achieved through conductive fiber or yarn. An electronic fabric sensor is free of gel and is thus called a dry sensor. With a signal-to-noise ratio comparable to a silver chloride electrode, it can provide accurate clinical parameters. It is comfortable to wear for long-term electrocardiogram (ECG) monitoring [10]. Moreover, the electronic fabric can also provide a flexible conductive network which provides a fundamental connection platform to enable a wired body area network (BAN) [11].

Smart clothing represents a new wearable technology with seamless integration of electronic fabric and miniature wearable devices. Its technical principle relates to multiple research areas such as design of washability, manufacture of textile dry electrodes, low power wireless communications, body sensor networks, microelectronic technology, and tele-medicine. This is an interdisciplinary subject, and the combination of smart clothing, cloud computing, big data, and machine learning technologies, which all have rapid developments in recent years, can greatly facilitate the development of health monitoring systems for long-term and real-time monitoring of human health.

2.2. Traditional wearable device for health monitoring

After breakthrough progress of micro-embedded systems, micro-electromechanical systems (MEMS), intelligent materials, wireless communication technology and micro sensing technology, the health monitoring system based on wearable computing has received extensive attention in academic institutions and industry. Previous work focused on physiological signals' acquisition, transmission and storage. Recently, emphasis has been on adopting wearable technology in a long-term, real-time health monitoring system through cloud computing, big data and machine learning technologies.

The wearable devices enabling long-term monitoring of human health have a great impact on the improvement of service levels of the healthcare industry. For example, as the global population aging problem becomes more serious, many countries in the world will have to deal with one challenge: how to provide high quality healthcare service for an aging population. The health monitoring system based on wearable technology is an effective solution to this problem. Because it can provide long-term monitoring of each physiological indicator of elderly people, it can predict various health tendencies of the elderly people and be used for disease prevention, diagnosis, and improve the quality of life. For chronic illnesses such as cardiovascular disease, hypertension, and diabetes, the health monitoring system based on wearable technology can be used for healthcare instruction and real-time treatment.

Although some useful attempts have been made in the field of health monitoring, there are many open problems that need to be resolved. As shown in Table 1, recent wearable health monitoring devices adopted by communities are mainly wrist watches, bracelets, heart rate belts, and fall detectors, but they are deficient in the following aspects.

- *Short Service Cycle*: The service cycle of these devices are mostly 2 to 3 months, which is due to the insufficient data accuracy. Taking fall detection of elderly as an example, the data acquisition of a fall detector is single point-based and frequent false alarms could be triggered. Also the results are still not accurate even in combination with heartbeat measurements. So the users will lose their confidence about such products after a brief period.
- *Insufficient Data Types*: Currently available products on the market can only collect few kinds of physiological signals in relation to healthcare, and have limited applications in health monitoring and medical treatment.
- *Data Accuracy Issue*: The physiological signals collected by existing wearable products have difficulty to reach the hospital standards. Consider the intelligent bracelet as an example. Heart rate is the most valuable physiological indicator it collects, but it has very limited applications in the healthcare industry. In addition, the bracelet cannot collect physiological data that are widely used in the field of healthcare, such as ECG signals, while other portable ECG collection devices are often complex and cumbersome to use.

User privacy protection is also an important issue yet to be properly addressed. A participant coordination based architecture and work flow was first proposed to successfully protect user privacy [12,13]. Furthermore, incentive mechanisms can encourage people to participate in the data collection process. A comprehensive survey of the existing research status and future directions can be found in [14].

In summary, even though wearable technologies have been applied to some extent in the field of health monitoring, the problems mentioned above need to be addressed in order to achieve their successful applications in the fields of disease diagnosis, chronic disease surveillance, and personalized, value-added health service.

3. SVSC: sustainable vital sign collection through smart clothing

3.1. SVSC system architecture

We present the proposed sustainable vital sign collection through smart clothing (SVSC) technique in this section. The system architecture of SVSC is shown in Fig. 1. Fig. 1 shows the collection and process of signals. Firstly, the users confirm the healthcare application scenario, such as medical monitoring of chronic patient. Then, Using smart clothing to collect physiological signals (e.g., ECG signals, heart rate). These signals will be transmitted to the healthcare cloud through cellular network or WiFi. The healthcare cloud can provide services, such as medical consultation.

We describe each key component of SVSC in the following.

3.2. Healthcare application scenarios

In the healthcare application scenarios based on smart clothing, end users who need health monitoring (such as those suffering from chronic disease, driver, autism patient, and empty nester), wear smart clothing in their daily lives. The smart clothing will collect users' physiological data. Although a variety of sensors have been integrated into the clothing, users will not be aware of the existence of the acquisition equipment woven in the clothes. The signal acquisition subsystem collects a number of users' physiological signals through micro pluggable modules of smart clothing. These original physiological signals will be preprocessed in a data collection terminal (e.g., for signal amplification and signal denoising) before they are uploaded to the cloud platform [15].

The users' current health data can be obtained after processing and analysis of physiological signals in the cloud platform. The disease or health conditions can then be predicted by the analysis of mass historical data with big data analytics. According to the analysis results, users can be informed of their health conditions. Also users will be provided with personalized health services through appropriate means. For example, the system will inform medical first-aid agencies or users' family members right after it detects a sudden heart attack. If there is a household healthcare robot, it will apply first-aid medicine to the patient to reduce safety risks right away. For users in need of mental health care, emotional comfort (such as voice reminders and soothing music) will be provided when negative emotions are detected. If an interactive robot is so equipped, it can derive the users' emotional state and follow affective interactive instructions from the cloud platform to have more affinitive emotional interaction with the user [16,17].

3.3. Communications

The communications of smart clothing include inner-communications and beyond-communications. The inner-communication refers to the communication model between sensors of the smart clothing via wired or wireless connection. The beyond-communication transmits the data collected by the smart clothes directly to the external environment through the cellular network or WiFi. These two communication methods are complementary. When an external application requires certain physiological signals, the application should send the instructions to the smart clothes through external communications firstly. Then the smart clothes will implement internal communication to collect relevant signals according to the instructions. In addition, when the sensors complete the collection of signals, these data will be firstly transmitted to the smart clothing to be gathered through internal communications, then transmitted to the external environment through external communication.

Table 1
Comparison of wearable health products.

Production name	Comfort index	Usability	Machine wash	Accuracy	Sustainability	Physiological index	Real-time operation
Smart bracelet (smart band)	High	Very easy	No	Low	Yes	Simple	Yes
Smart watch	High	Very easy	No	Low	Yes	Simple	Yes
ECG monitoring instrument	Low	Hard	No	High	Yes	Simple	No
Heart rate monitor	Middle	Easy	No	High	No	Simple	No
Fall detection device	Middle	Easy	No	Low	No	No	Yes
EPIC smart clothing	High	Very easy	Yes	High	Yes	Complex	Yes

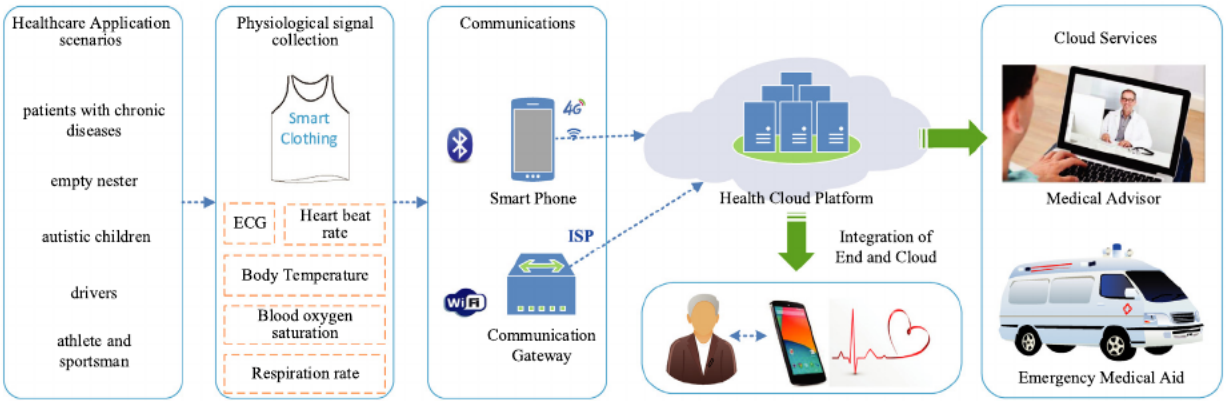


Fig. 1. Sustainable vital sign collection system architecture.

3.4. Cloud platform

After collecting data from users, data preprocessing, machine learning and deep learning will be used to establish medical detection system in order to realize real-time detection and analysis and provide medical services for users. In order to realize real-time detection, analysis and provide medical services for users, first, we need collect data from user. Then, after data preprocessing, we use machine learning and deep learning to establish medical detection system. For example, if we want to make emotion detection for empty nest elderly. First, we should analyze the type of data that needs to be collected. In this situation, we need to collect the heartbeat information, body temperature and ECG signal. Then, We use machine learning to identify users' emotions. Finally, we can feedback the results to a user's family or a hospital. Therefore, in this case, in order to realize real-time monitoring, the data collected by the user will be analyzed in real time, and it will be fed back in time. Furthermore, in order to improve the accuracy of the test, the system will also ask the user to offload other data which include user location, indoor environment, social network data to improve the accuracy [18].

3.5. Integration of end and cloud

With the development of a specialized cell-phone application program, it is convenient to integrate the users' social network data, location information, cellphone call records, and so on. These offer emotion-aware data in a physical space for the health cloud platform. The specific implementing approach is to store the emotion model, which is based on physical data training on the cloud platform, to establish a sole sign for the emotion model of each user, and then to transmit the user's ECG signal to the cloud platform through the smart clothing with ECG collection and transmitting functions. The cloud platform conducts real-time analysis and disposal of the received ECG data, and makes use of the previously trained model to predict user's emotion state according to the user's sole sign (other data collected on the cloud platform can assist emotion detection). When a detection result shows that the user has a negative emotion, the system will call for related device and resources for some emotional interaction with the user. For example, if a user is in a sad mode, the system will play a relieving music through the cell-phone. It can also send orders to the robot at home, which will make emotional interactions with the user through a series of actions and its voice, to eventually realize effective emotion care.

3.6. Physiological signal collection

Smart clothing can collect a number of physiology signals, including ECG, body temperature, blood oxygen saturation and heart rate. The physiological signals of the collections are different according to the scene. For example, when detecting a patient with a heart disease, it is necessary to get a ECG signal, heart rate information, and so on. Then judging the health of the heart by electrocardiogram analysis. However for the detection of hypertension such as chronic disease, the daily detection including blood pressure, blood oxygen and so on. Therefore, after user setting the application scene, the corresponding type of signal acquisition can be set. The introduction of these signals is as follows:

- ECG Signal: This is an important physiological indicator of the human body, which plays an important role in health assessment and disease diagnosis. Considering the tradeoff between appearance and signal accuracy, smart clothing contains textile dry electrodes instead of traditional medical electrodes and can integrate 2–3 textile dry electrodes. Therefore, electrode LA(left arm) and RA(right arm) belong to multiplex electrode and are also used to measure the respiratory signal.
- Blood oxygen saturation: Blood oxygen saturation is collected by using an optical measurement method. The measurement is based on the principle that the amount of light absorbed by the arterial blood varies with the arterial pulses. Through the reflective blood oxygen sensor, which is integrated on the inner side of the cuff of smart clothing, the acquisition of Blood oxygen signal is accomplished.

- Body temperature: The body temperature is measured by a temperature sensor based on a negative temperature coefficient (NTC) thermistor. The sensor is integrated in the armpit of the smart clothing.
- Heart rate: The heart rate can be measured from the measured ECG signal.

4. SCAI: smart clothing for affective interaction

Virtual Reality (VR) was originally applied in the games and entertainment industry. However, it has exhibited great potential in healthcare, education, military, manufacturing, and other industries. Taking the healthcare scene as an example, the calculation of real-time processing will be more than complex without VR technology. However, the VR technology can provide realistic experience for users and real-time feedback. In order to achieve emotional interaction, we use smart clothing as a link between VR and the user. The details will be described as following. With the smart clothing technology, various sensing devices are integrated into ordinary clothes. Smart clothing makes a seamless connection between clothing and VR devices, so as to simplify the physiological and action signal acquisition. It has be recognized that smart clothing might bring about the wide application of VR in the future healthcare industry. For example, in physical rehabilitation training for stroke, fractures, and other diseases, smart clothing will transmit all the rehabilitation training data to the VR devices (VR glasses/helmets). The VR devices captures the human body motion from the data. It can also carry out gait analysis and virtual human body motion simulation. Finally, VR devices display the user's actions and physiological changes on a real-time basis. This means that the patient can master his/her own training intensity and effects, so as to realize self-rehabilitation. Next, the rehabilitation training data produced by VR are transmitted to the physician as an aid in diagnosis and treatment [19].

5. Testbed and experimental study

5.1. Smart terminal design for body signal collection

The block diagram of the operation of a smart collection terminal is shown in Fig. 2. We choose the TP4056 linear lithium-ion battery as a power supply system and the LM317 voltage regulator circuit to adjust the voltage from 3.7 V to 3.3 V. We are also equipped with AD8232 sensor for the collection of ECG and other bio electricity signals, which can be measured from RA (right arm), LA (left arm), RL (right left), respectively. Amplify these signals to 400 times and use the filter to get the signals between 0.05HZ and 125 Hz. STM32L152RBT6 STMicroelectronics ARM microcontroller can be applied to analog-to-digital conversion and it also has the virtue of good support for Universal Asynchronous Receiver/Transmitter, which is one of the reasons that we choose this kind of equipment. HC-05 represents the Master–slave Bluetooth serial port module, which is the key module of data transmission and communication. [20]

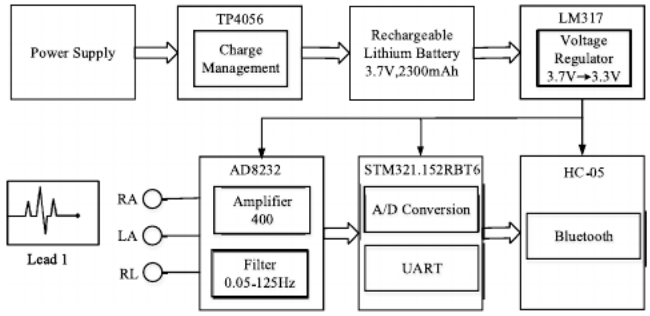


Fig. 2. Schematic of a smart collection terminal.

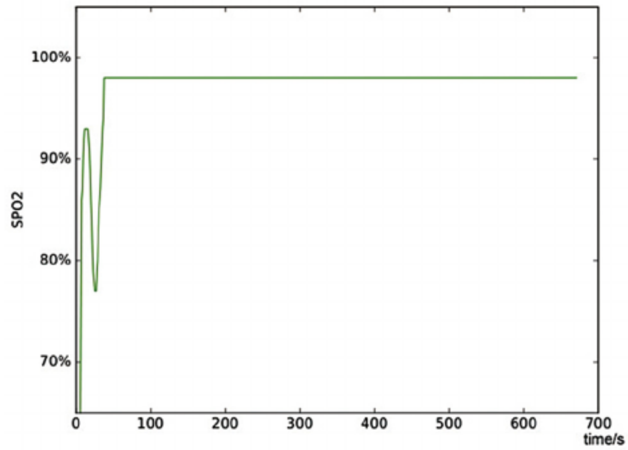


Fig. 3. Oxygen saturation data from smart clothing.

5.2. Measurement of blood oxygen saturation and body temperature

Blood oxygen saturation is measured with a noninvasive measurement method. Using a 660 nm wavelength red light and 940 nm infrared light as incoming light sources, it estimates blood oxygen saturation by measuring the light intensity through the fabric of clothes. In the experiment, the sensor needs a short period of time for stable results, while the sensor is in contact with the skin. Therefore the brief transient phase occurs at the beginning, as shown in Fig. 3. After the transient phase, the measurement result of the sensor becomes stable at a value of 98%, which is the human body's normal blood oxygen saturation value.

The measurement of body temperature is achieved by the NTC Thermistor, which is also the sensor component of a medical digital thermometer. In the temperature range from 33 °C to 45 °C, the temperature is linear with the voltage on the thermistor of the sensor. As shown in Fig. 4, the sensor is not in contact with the skin from time 0 s to 100 s, and therefore the temperature is shown to be 0 °C. Voltage does not have a linear relationship with temperature at this range. From 100 s to 300 s, the thermistor and temperature exhibit a negative linear relationship. With a rising temperature, the voltage decreases. In order to observe the relationship between body temperature and voltage in a more convenient way, the range of the temperature change is enlarged so that the body temperature is rising as shown in the figure. After 300 s, the sensor is separate from the skin. Therefore, the temperature returns to zero.

5.3. Effect of number of electrodes on ECG signal collection

5.3.1. Impact of body gestures on ECG signal measurement

We tested and verified the ECG monitoring with different lead numbers, as well as the effect and reliability of ECG monitoring under different postures, which involve different poses and deep breathing. In the tests, 2-lead and 3-lead are used, respectively. In regards of postures, three situations, including sitting, standing, and marching on the spot, are tested separately, as shown in Fig. 5. The captured ECG signals are presented in Figs. 6 and 7. ECG signals presented by the postures in the case of deep breathing are tested as well.

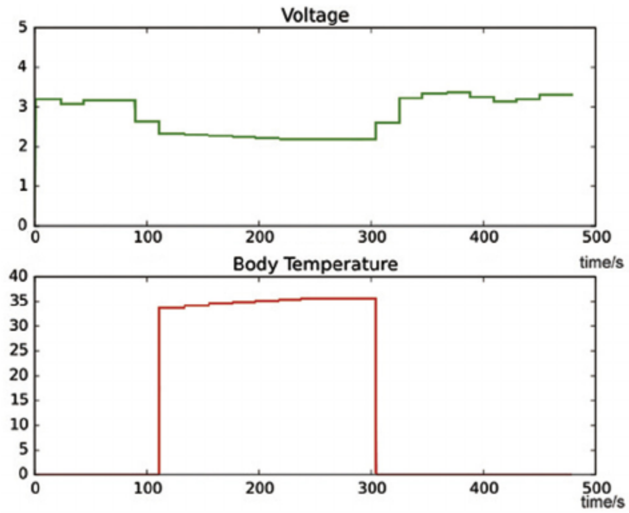


Fig. 4. Body temperature data from smart clothing.

(a) (b) (c)

Fig. 5. Three postures for collecting ECG signal: (a) standing, (b) sitting, (c) march on the spot.

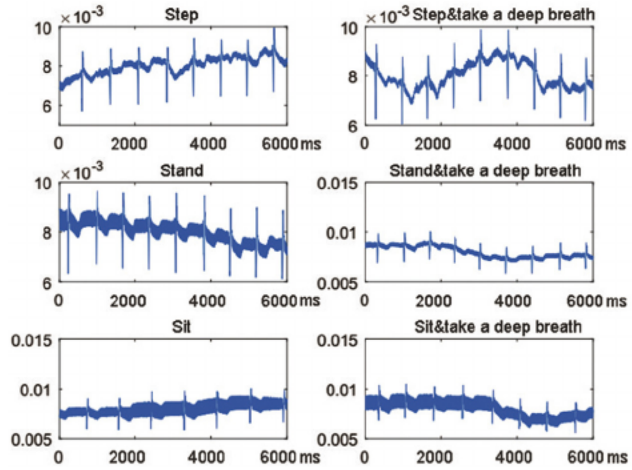


Fig. 6. Waveform of a 2-lead ECG signal from smart clothing.

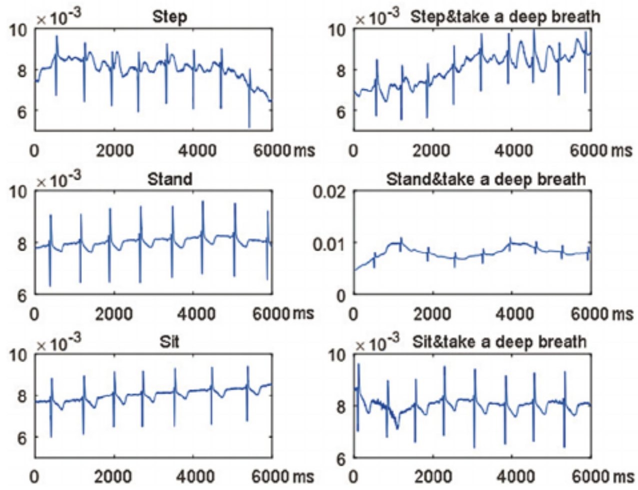


Fig. 7. Waveform of a 3-lead ECG signal from smart clothing.

First, one can observe by comparing Figs. 6 and 7 that the ECG waveform captured in the 2-lead case has more blurs and larger noises, while the waveform captured in the 3-lead case barely has any obvious noise. The high-frequency noises in the 2-lead ECG waveform can be filtered with some digital method, but it will cause lose of a part of the energy of the effective signal. As shown in Fig. 7, the left column of three figures present the data of ECG monitoring in situations including sitting, standing, and marching on the spot. And the three figures on the right column correspond to the different postures in the case of deep breathing. It can be observed that the ECG moves sharply (i.e., with Baseline Drift) due to deep breathing. This is caused by interfering factors such as skin EMG and so forth. To reduce the impact of deep breathing, the right figures can be preprocessed with a series of digital signal processing techniques. Confirmed by our tests, the system can be used for long-term ECG monitoring, and the 3-lead approach has a better effect and is more amenable to the later processing analysis.

5.4. Smart clothing based ECG monitoring

In our implementation of the ECG monitoring demo, we choose smart clothing using two fixed electrodes and one optional electrode to reduce cost and complexity. First, we integrate the high comfort textile dry electrodes into close-fitting clothes, and the flexible conductors connecting to two electrodes, respectively, to a snap fastener. The ECG acquisition module and transmission module will collect ECG signals from the snap fastener. Finally, the ECG transmission module will transmit the collected ECG signals to mobile phones, personal computers, or the cloud via a wireless connection.

Since the ECG signal strength of the human body is relatively weak, and it is particularly susceptible to interference from the surrounding environment and the body itself (for example, interference caused by body movements), many kinds of interference noises exist in the original ECG signal. Such noises have a large impact on the medical application and sentiment analysis of the collected ECG signals. In addition, because the collected ECG signal is similar to a continuous-time signal, the user's ECG characteristics information cannot be obtained from the original ECG data. But the characteristics of these ECG data are essential to sentiment analysis. Therefore, firstly we must pre-process the original ECG signal and eliminate interfering signals. The proposed ECG signal processing procedure is shown in Fig. 8, and will be discussed in detail in the following.

5.4.1. ECG signal preprocessing

Noise from ECG signal is composed of power frequency interference, electromyographical interference, baseline drift, electromagnetic noise, and so on. The ECG signal frequency range is

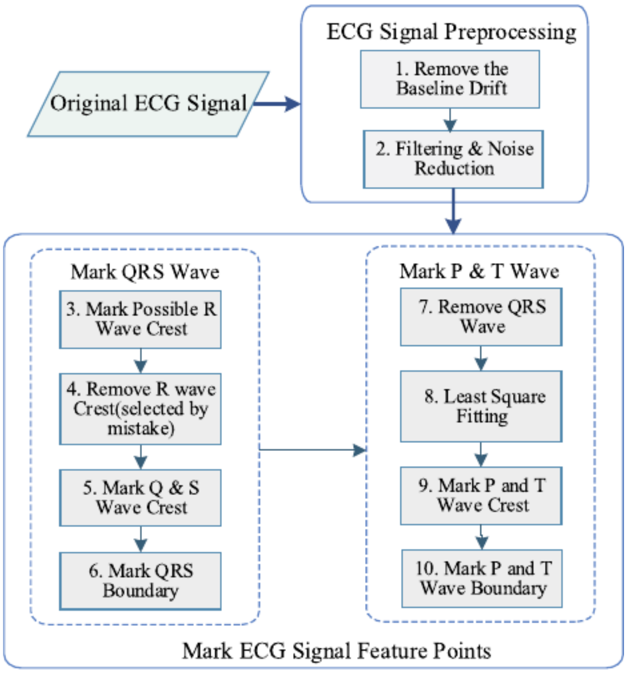


Fig. 8. ECG signal processing flow.

between 0.01 Hz $\sim$ 100 Hz, and more than 90% of the energy in the ECG signal is concentrated in the frequency range of 0.25 Hz $\sim$ 35 Hz. The original ECG signal is a continuous-time signal. Fourier transform and wavelet transform are two commonly used tools for time-domain signal processing. Fourier transform only retains the frequency domain information instead of the time-domain information, while wavelet transform retains frequency domain information and time-domain information at the same time. In addition, wavelet transform offers superior temporal resolution for the high frequency components and higher resolution in frequency for the low frequency components, which conforms to the resolution requirements of ECG signal analysis in both high and low frequency ranges. We can exploit the above characteristics for ECG signal pre-processing.

The preprocessing of ECG signal is divided into two processes: (i) removal of ECG baseline drift and (ii) removal of noise (as shown in Steps 1 and 2 in Fig. 8). The removal of the ECG baseline drift can be achieved by setting the approximate parameters of the transformed wavelet as the mean value of the parameters. High frequency noise can be removed by deleting the details of the first and the second layers of the transformed wavelet. This is because the D1(first diagonal) and D2(second diagonal) frequencies are mainly distributed in 60 Hz $\sim$ 180 Hz, but the effective ECG waveform is not in this range. Thus, the two kinds of details can be directly removed.

5.4.2. *QRS (the combination of three of the graphical deflections) wave group detection*

After preprocessing the ECG signal, further feature detection is applied for recognizing the QRS wave group. The QRS wave group includes several major components, such as the QRS wave crest, the Q wave, and the R wave.

The QRS wave group reflects the electrical excitation of the left and right ventricles during the depolarization process. The first downward (negative) wave coming after the P wave at the baseline is called the Q wave, the first upward (positive) wave is the R wave, and the downward wave after the R wave is the S wave. The width of the QRS wave group indicates the time limit of the QRS wave, which represents the time required for all the ventricular excitation. The maximum duration for a normal person is no more than 0.11 s.

The detection of the QRS wave group is the basis of ECG band signal detection, and the detection of the R wave crest is the basis of QRS wave group detection. To begin with, we calculate the first order differential of the ECG signal after pretreatment. Then we set a first-order difference threshold: if the value of the first-order difference is larger than the threshold, the point may exist in the rising part of the R wave. According to this characteristics, we can identify the R wave crest. However the R wave crest we find may be an incorrect choice, which will need to be removed. The R wave could not appear twice in 0.25 s; hence, it is necessary to select from the two peaks that appear within 0.25 s. We compare the amplitudes of the two waves. The wave with a larger amplitude should be the actual R wave crest, and that with a smaller amplitude is not the true selection of the R wave crest. Next, we use the selected R wave crest to identify the Q and S wave crests. To do that, we must search for the extremes on both sides of the R wave crest, and the minimum point is the Q or S point.

5.4.3. *PT wave detection*

The P wave reflects the electrical excitation of the left and right heart atrium during the depolarization process. The first half is mainly generated by the right atrium, and the second half is mainly generated by the left atrium. The width of a normal P wave does not exceed 0.11 s, and the maximum rate is no more than 0.25 mv. The T wave reflects a potential change of the ventricular repolarization process. In an ECG mainly composed of an R wave, the T wave amplitude should not be less than 1/10 of the R wave.

PT wave detection relies on the detection of the QRS wave group. This method still tries to find the first-order difference on a smooth curve, according to the zero crossing point of the first order difference to identify the crest; then depending on the information on the position and amplitude, we can confirm the position and crest of the PT wave. This is shown in Steps 7 $\sim$ 10 of Fig. 8.

The detailed process of PT wave detection is provided as follows.

- Remove the detected QRS wave group signal from the original ECG signal. At this time the original ECG signal is divided into several segments on the PT wave by the appearance of the QRS wave group.
- There is a P wave and a T wave in every segment. After noise reduction, there are still a lot of small high-frequency noises in each segment. This will make the zero-crossing point of the first order difference unavailable. Therefore, we use the minimum square fitting for each segment for curve fitting, which will make the line segment smooth and reflect the changes of the curve at the same time.
- After the minimum square fitting, we can feed the first order difference to the fitting function and take the zero-crossing point of the first order difference as a possible PT wave crest.
- Then both sides of the vertex are sought to find the minimum value of the fitting curve, while taking the vertex as the center and using a certain coefficient of contraction to determine the boundaries of the PT wave.
- The next step is to determine the true PT wave according to the amplitude and position of the wave. (i) The amplitude of the PT wave should be larger. (ii) The P wave is on the right side, and the T wave is on the left side. The most effective PT wave can be selected from the possible PT waves.

Table 2
Comparison test between data collection of smart clothing and that of an ECG simulator.

No	Simulator A			Simulator B		
	Smart clothing	Simulator	Error%	Smart clothing	Simulator	Error%
1	60	60	0.00%	60	60	0.00%
2	75	75	0.00%	75	75	0.00%
3	100	100	0.00%	100	100	0.00%
4	120	120	0.00%	119	120	−0.83%
5	150	150	0.00%	150	150	0.00%
6	200	200	0.00%	200	200	0.00%
AVG	705	705	0.00%	704	705	−0.14%

5.4.4. Accuracy verification

In order to verify the accuracy of physiological signals collected by smart clothing, the following two methods can be applied.

- A comparative test based on the ECG simulator: connect the ECG electrodes of the smart clothing to the ECG simulator to compare the difference between the data of the simulator and that from smart clothing, in the form of difference in measured heartbeats. We have selected 2 ECG simulators to do this test.
- A comparative test based on the real tests with volunteers (with half men and half women). We collect their heartbeats information before, during, and after the experiments. At the same time, we make a comparison to the heartbeats measured by the ECG signals.

The above experimental results show that the heart rate obtained through smart clothing matches the results measured by the simulator or the electrocardiograph. Table 2 lists the comparison results of smart clothing and the two kinds of ECG simulators. It can be seen the inmost cases the error is 0%, and in several few cases the errors are non-zero but still negligible.

5.5. Emotion detection

The ECG signal is strongly linked to human emotion, so we can use the signal to analyze human's feelings [21]. Extracted ECG features can be used for emotion detection, and then for sentiment detection.

We invited four students to take part in the data acquisition experiment. The results are as follows. All the waveform graphs of ECG signals are generated from the ECG data collected by smart clothing they ware. In particular, the scenario that a student is reading in a calm state, while we also compare the ECG signals generated when the students are walking rapidly. Through the emotion analysis of the ECG data after the experiment, we find that the ECG graphic corresponding to each emotion is different. The emotional data of the students are also collected accordingly. The signal wave exhibits a relatively larger fluctuation when the user feels angry. The fluctuation is relatively smaller since the user is happy. When the user is in a depressed mood, the value of the waveform valley is quite small. Finally, we illustrate the signal waveform when the user is relaxed and calm.

5.5.1. ECG signal feature extraction

By labeling the P-QRS-T wave and other feature points in the ECG signal, we can extract features that can be used for training the machine learning classification algorithm. The application of emotion recognition needs to extract the features including the intervals and amplitudes of the P-QRS-T waves. The procedure is described below.

- *PR interval:* This is the time interval between the starting point of the P wave and the starting point of the QRS wave group, which is indicative to the time from the beginning when the heart is in atrium excitation to the beginning when the heart is in ventricle excitation. This is an important indicator of the relationship between the atrium and the ventricle.
- *QT interval:* This is the time between the beginning of the Q wave and the end of the T wave, representing the time of ventricular depolarization and repolarization.
- *ST segment:* This is the segment from the end of the QRS wave group to the beginning of the T wave, referring to the slow phase of the ventricular repolarization.
- *PR segment:* This is the segment from the end of the P wave to the beginning of QRS wave group, primarily reflecting the conduction of the excitation in the atrioventricular node.
- *QRS wave group:* The time limit of the QRS wave group, i.e., the width of the QRS wave group, which represents the time required for the whole ventricular muscle excitation process.

When people are in different emotional states (or when the emotional state changes), the value of the above features of the ECG signal are not the same (or will be obviously changed). Therefore, based on the feature data extracted from the ECG signal, the machine learning classification algorithm can be used to realize the detection of emotional states.

Table 3
ECG sample data statistics.

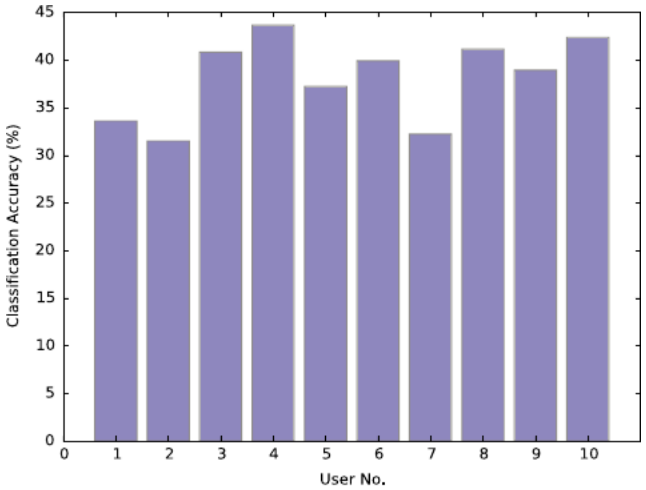
Volunteer No.	Number of samples (Under different emotional states)				
	Normal	Happy	Angry	Fear	Sad
User_1	92	69	34	26	18
User_2	93	48	33	35	27
User_3	83	41	30	44	31
User_4	85	79	31	33	30
User_5	89	62	12	43	32
User_6	78	37	11	20	12
User_7	99	71	27	31	23
User_8	94	49	18	40	19
User_9	96	39	15	37	16
User_10	89	52	32	19	24

5.5.2. Sample data collection

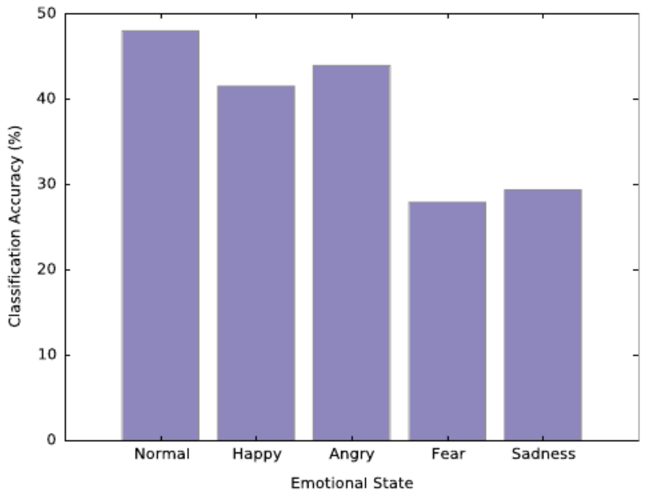
In order to test the performance of the proposed system, 10 volunteers (including four men and six women, aged from 23 to 30 and with an average age of 25.2) were recruited so that we could test their ECG signals using smart clothing. The collected ECG signals are tagged with emotional states (based on the original emotion proposed by Krech et al. [22]). The detailed statistics from the samples are presented in Table 3.

5.5.3. Emotion detection evaluation

We separate the collected ECG sample data of each volunteer to the training set (70%) and testing set (30%). We extract the features separately, and then use support vector machine [23] to train the training set and generate the classification model. Finally, we apply



(a) Affective detection accuracy based on user.



(b) Average affective detection accuracy.

Fig. 9. User-based emotion detection accuracy.

the testing set to the trained classification model to perform the classification test [24–26].

The accuracy of emotion prediction for these 10 users is presented in Fig. 9(a). [27] We can see that the accuracies of User_2 and User_7 are relatively low (i.e., 31.5% and 32.2%, respectively), and the average value of the accuracy of the user's emotions predictions is 38.1%. The average accuracy of emotion detection based on the emotional state is shown in Fig. 9(b). There are different numbers of samples for different emotions in the collected sample data, which may affect the accuracy of the model outputs during the training, and may lead to different accuracies of emotion recognition. The accuracy of emotion detection rates for normal, happy, and angry are higher than 40% (48%, 41.5%, and 43.9%, respectively), and the accuracy for fear and sad are 27.9% and 29.3%, respectively [28–32].

6. Conclusion

In this paper, what we do is to compare smart clothing with traditional wearable devices and analysis various advantages of smart clothing. We summarize the design architecture, the applicable scenarios and the implementation methods of smart clothing. Smart clothing can collect a variety of body signs data such as temperature, blood oxygen, ECG signals, and analysis the user's physical state using these data. Smart clothing collects the ECG signals and get precise ECG signals by steps of ECG signals preprocessing, QRS waveform group detection and PT waveform detection. We realized the emotion detection, in which the accuracy of result of happy emotion, angry emotion, fear emotion and sadness emotion are 48%, 41.5%, 27% and 29.3% respectively.

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Long Hu received his Ph.D degree in computer science from Huazhong University of Science and Technology (HUST), China, 2017. He has also received his Master and B.S. degree in HUST. He is the Publication Chair for 4th International Conference on Cloud Computing (CloudComp 2013). Currently, his research includes 5G Mobile Communication System, BigData Mining, Marine-Ship Communication, Internet of Things, and Multimedia Transmission over Wireless Network, etc.

Jun Yang received Bachelor and Master degree in Software Engineering from HUST, China in 2008 and 2011, respectively. Currently, he is a Ph.D candidate at Embedded and Pervasive Computing (EPIC) Lab in School of Computer Science and Technology, HUST. His research interests include cognitive computing, software intelligence, Internet of Things, cloud computing and big data analytics, etc.

Min Chen (SM'09) has been a Full Professor with the School of Computer Science and Technology, Huazhong University of Science and Technology (HUST) since February 2012. He is the Director of the Embedded and Pervasive Computing (EPIC) Lab, HUST. He is Chair of the IEEE Computer Society (CS) Special Technical Communities (STC) on Big Data. He was an Assistant Professor with the School of Computer Science and Engineering, Seoul National University (SNU). He worked as a Post-Doctoral Fellow with the Department of Electrical and Computer Engineering, University of British Columbia (UBC), for three years. Before joining UBC, he was a Post-Doctoral Fellow with SNU for one and half years. His research focuses on Cyber Physical Systems, IoT Sensing, 5G Networks, Mobile Cloud Computing, SDN, Healthcare Big Data, Medica Cloud Privacy and Security, Body Area Networks, Emotion Communications and Robotics, etc. Prof. Chen was the recipient of the Best Paper Award from QShine 2008, IEEE ICC 2012, ICST IndustrialIoT 2016, and IEEE IWCMC 2016. He serves as Editor or Associate Editor for Information Sciences, Information Fusion, and IEEE A CCESS , etc. He is a Guest Editor for IEEE Network, IEEE Wireless Communications, and the IEEE T RANSACTIONS ON S ERVICE C OMPUTING , etc. He was Co-Chair of the IEEE ICC 2012—Communications Theory Symposium and Co-Chair of IEEE ICC 2013—Wireless Networks Symposium. He was General Co-Chair for IEEE CIT—2012, Tridentcom 2014, Mobimedia 2015, and Tridentcom 2017. He was the Keynote Speaker for CyberC 2012, Mobiquitous 2012, Cloudcomp 2015, IndustrialIoT 2016, and The 7th Brainstorming Workshop on 5G Wireless. He has more than 300 paper publications, including 200+ SCI papers, 80+ IEEE T RANSACTIONS /J OURNALS papers, 18 ISI highly cited papers and 8 hot papers. He has four books: OPNET IoT Simulation (2015), Big Data Inspiration (2015), 5G Software Defined Networks (2016) and Introduction to Cognitive Computing (2017) with HUST Press, a book on big data: Big Data Related Technologies (2014) and a book on 5G: Cloud Based 5G Wireless Networks (2016) with the Springer Series in Computer Science. His latest book (co-authored with Prof. Kai Hwang), Big Data Analytics for Cloud/IoT and Cognitive Computing (Wiley, U.K.) was published in 2017. His Google Scholars Citations reached 12,000+ with an h-index of 54. His top paper was cited 1100+ times. He was the recipient of the IEEE Communications Society Fred W. Ellersick Prize in 2017.

Yongfeng Qian received the M.S. degree in Huazhong University of Science and Technology, China, in 2015. She is currently a Ph.D. candidate in Embedded and Pervasive Computing lab led by Prof. Min Chen in School of Computer Science and Technology at Huazhong University of Science and Technology. Her research includes Internet of Things, Big data analytics, network security and data privacy.

Joel J.P.C. Rodrigues [S'01, M'06, SM'06] is a professor and senior researcher at the National Institute of Telecommunications (Inatel), Brazil and senior researcher at the *Instituto de Telecomunicações*, Portugal. He has been professor at the University of Beira Interior (UBI), Portugal and visiting professor at the University of Fortaleza (UNIFOR), Brazil. He received the *Academic Title of Aggregated Professor* in informatics engineering from UBI, the Habilitation in computer science and engineering from the University of Haute Alsace, France, a Ph.D. degree in informatics engineering and an MSc degree from the UBI, and a five-year BSc degree (licentiate) in informatics engineering from the University of Coimbra, Portugal. Prof. Rodrigues is the leader of the Internet of Things research group (CNPq) and of the NetGNA Research Group, Director for Conference Development—IEEE ComSoc Board of Governors, IEEE Distinguished Lecturer, the President of the scientific council at ParkUrbis—Covilhã Science and Technology Park, the Past-Chair of the IEEE ComSoc Technical Committee on eHealth, the Past-chair of the IEEE ComSoc Technical Committee on Communications Software, Steering Committee member of the IEEE Life Sciences Technical Community and Publications co-Chair, and Member Representative of the IEEE Communications Society on the IEEE Biometrics Council. He is the editor-in-chief of the International Journal on E-Health and Medical Communications, the editor-in-chief of the Recent Advances on Communications and Networking Technology, the editor-in-chief of the Journal of Multimedia Information Systems, and editorial board member of several high-reputed journals. He has been general chair and TPC Chair of many international conferences, including IEEE ICC, IEEE GLOBECOM, and IEEE HEALTHCOM. He is a member of many international TPCs and participated in several international conferences organization. He has authored or coauthored over 550 papers in refereed international journals and conferences, 3 books, and 2 patents. He had been awarded several Outstanding Leadership and Outstanding Service Awards by IEEE Communications Society and several best papers awards. Prof. Rodrigues is a licensed professional engineer (as senior member), member of the Internet Society, and a senior member ACM and IEEE.