Accurate Cirrhosis Identification with Wrist-Pulse Data for Mobile Healthcare

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ABSTRACT

In recent years, mobile healthcare has received increasing attention. As the wrist-pulse diagnosis in traditional Chinese medicine(TCM) only needs the wrist pulse information of a patient, without any other physiological data and invasive checking, it is a promising technique for mobile healthcare in terms of cost and convenience. But the pulse-based diagnosis requires the sophisticated and long-term training of the physicians. So it is urgent to develop a digitalized method to objectify and standardize the pulse-based diagnosis process. In this paper we design a wrist-pulse sensing and analyzing prototype system which involves a general pulse-sensing device and a cirrhosis diagnosis scheme based on the captured pulse information. The experimental results show that the accuracy of the proposed system reaches to 87.09% in cirrhosis identification.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

Keywords

mobile healthcare, pulse diagnosis in TCM

1. INTRODUCTION

In recent years, mobile healthcare has received increasing attention and many healthcare systems [10, 7, 5, 1] have been developed because they can provision personalized and professional heathcare services to users in a flexible, convenient manner, saving the constrained public medical resources and reducing the medical costs of users. The traditional Chinese pulse diagnosis (TCPD) is a much desirable choice in mobile healthcare applications. TCPD has been successfully used in China for at least two thousand years [6], and is becoming more and more popular all over the world (for example, most Asian countries and Australia). Compared with the physiological data based diagnosis, TCPD can be used to diagnose a large amount of diseases such as heart disease, cirrhosis, etc., without turning to any specialized medical device, and only with feeling the radial artery of patient's wrist, as shown in Fig.1. The traditional Chinese medicine theory behind wrist-pulse based diagnosis relies on such fact—the blood flows through different organs, with different rates which may reflect different health status and can be identified according to the pulse fluctuation pattern [22]. Therefore the TCPD will be a more competitive method for mobile healthcare applications.

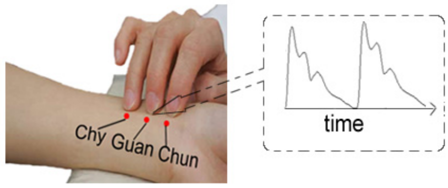

Figure 1: The illustration of diagnosis based on wrist pulse

In fact the wrist pulse is a sort of physical signals, vibration signals for traditional Chinese medicine physicians. As shown in Fig.1, the physicians use their tips of the index, the middle and the fourth fingers to feel the pulse fluctuation at three positions (denoted by "Chun", "Guan", and "Chy", respectively) within the radial artery area of the patient's left or right wrist. However such pulse-based diagnosis depends heavily on the experience and subjective sensing of the physicians. Two physicians may make completely different diagnosis results for the same patient. Therefore we need an objective standardized method of wrist-pulse waveform processing.

In this paper, we describe a novel pulse measuring system with intelligent data analysis. The system is based on the sensor technology and intelligent data analysis technology. One main task is developing a sensor which uses PVDF film to sense the pulse signals. The other is designing an automated algorithm to help diagnosing. With the system,we can measure the pulse signals at home and save our pulse signals permanently.

The rest of the paper is organized as follows. We first describe the related work on pulse monitoring system in Section 2. The design of the system is presented in Section 3. Section 4 discusses the analysis of the pulse signals starting with data collection, signal preprocessing, feature extraction and classification. Experiments to demonstrate the system effectiveness offered in Section 5. Section 6 is conclusions.

2. BACKGROUND AND RELATED WORK

2.1 Background

Medical practitioners of TCM consider that the pulse signal of radial artery can reflect an individual's state of health, so it can be used to assess health. The pulse wave has two important components [14]. The first component is the rise to the maximum pressure, and the second one is the tidal wave. The first rise wave will be followed by a slow decline with a notch and slight increase in pressure from aortic value closure, when the backflow of blood in the aorta overcomes the expulsion force of blood from the heart. The tidal wave is the result of reflect waves that are an echo of the initial primary wave traveling from the heart to the periphery. As the arteries become narrow in the periphery, the arterial resistance is increased, which causes the pulse wave to rebound and consequently causes a reflective wave to move back towards to the heart. In summary, the wrist pulse can be generally considered a traveling pressure wave that is caused by the rhythmic contraction and the relaxation of the heart.

TCM practitioners claim that certain position on the wrist is linked to the specific organ [6, 8]. For example, according to TCM , the signal variations of the Chun and the Guan positions on the left wrist can effectively reflect the conditions of the heart and the liver as well as the gall bladder, respectively.

2.2 Related Work

Many researchers have focused on implementing pulse monitoring systems with intelligent data analysis. Most of them employ sensors to sense pulse signals. Some of them design the graphic user interfaces.

In [23], the authors design a wrist-pulse waveform retrieval and analysis system with graphical LCD display. They design a wrist-watch-like structure attached over the radial artery area for wrist-pulse retrieval. They use pulse information retrieval unit to build a star wireless network. The gateway of pulse information retrieval unit is connected to a server which analyzes the wrist-pulse data and stores the data. Finally, the results can saved in a database locally or remotely.

The main contribution of [12] is that they design a noninvasive measuring apparatus which employs a standard positioning procedure to detect the optimal site for accurately measuring of the pressure pulse waveform. [12] also validates the effectiveness that the apparatus is suitable for the pressure pulse waveform.

In [2], a handheld SOC-based pulse monitoring system is built with intelligent data analysis, and it transmits physiological signals, via wired Internet interface, to a remote physiological database. The medical staff can observe the real-time pulse signals, assisted by the web-based interface.

In [3], a USB-based Doppler ultrasonic blood analyzer is used to collect the pulse signals; through the USB interface, the collected signals are transmitted and then stored in a PC for further processing and analyzing. The main contribution in [3] is a systematic method proposed to analyze the wrist pulse signals.

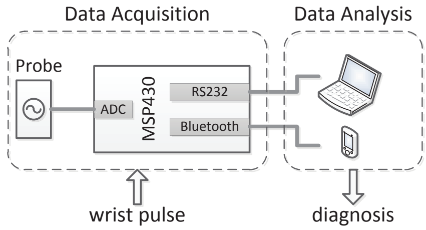

Figure 2: The architecture of our system

The content described above is the description of the pulse monitoring systems. Next we describe the application of classification methods in pulse diagnosis. Some researchers use classification methods to classify pulse types for further diseases diagnosis [15]. Since there are twenty-seven pulse types and each pulse type relates to some diseases [8]. Some researchers use classification methods to research certain disease [16, 17, 23]. However, the feature extraction methods in these papers are complicated. In this paper, we use classification method to discriminate healthy subjects from patients with cirrhosis. Moreover, we try to use binning method as feature extraction method which is a simple and time-efficient method.

We can see that the current pulse monitoring systems use the wired Internet to realize the remote pulse acquisition and processing. In this paper, we want to design a portable or mobilephone-based pulse-monitoring system that can realize wireless communication based on Bluetooth technology. With the system, the TCM staff can efficiently and easily participate in the medical services over communities.

3. THE PULSE-SENSING SYSTEM DESIGN

This section will present the design of the proposed system. Fig.2 shows the architecture of our system, which consists of two components in terms of data: data acquisition and data analysis. To obtain wrist pulse data more accurately and efficiently, we design a new pulse-sensing device, called probe, using the polyvinylidene fluoride (PVDF) material. We use the MSP430 microcontroller to sample the probe via ADC interface and transfer the raw pulse data into the values with engineering unit. Especially the MSP430-based MCU supports the RS232 serial communication and the Bluetooth, making our pulse-sensing device more flexible to be extended. For mobile healthcare systems, users usually focus on the performance of diagnosis, so we design an accurate cirrhosis identification scheme running on PCs or mobile devices such as mobile phone.

As shown in Fig.2, our system involves the pulse-sensing module and the diagnosis module. The pulse-sensing probe is attached closely to the radial artery area of the user's left wrist for pulse retrieval. The pulse information is transmitted, via wire or wireless channel, to PC or mobile phone for storage and analysis. In the followings we will detail the prototype of the proposed pulse-sensing system in hardware.

3.1 Probe Design

The wrist-pulse signal is very weak with low signal-noise-

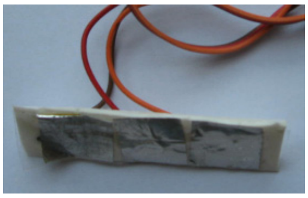

Figure 3: the probe

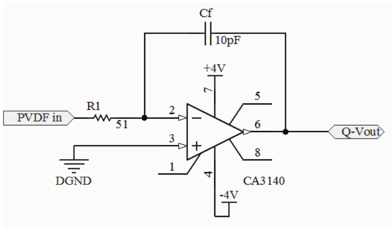

Figure 4: The amplifier circuit

ratio. In this paper we select the PVDF [11] as the sensor of wrist pulse due to the good piezoelectric and sensitive effect of PVDF materials. In particular, the PVDF is pretty soft and then can be attached to wrist much tightly. The PVDF easily results in strong ferroelectric effect (piezoelectricity) after being stretched. In essential, the piezoelectricity is a phenomenon when the elastic energy in a solid body is coupled with the dielectric energy in the same material. The piezoelectricity of PVDF can often be profiled with proportionality coefficients between mechanical and electrical values (or causes and effects). [13] provides more details about the principle that PVDF materials generate energy. In our probe design, we use a three-channel PVDF sensor of 30μm, the real probe is illustrated in Fig.3.

Since the sensitivity of PVDF is influenced by geometrical shape, the PVDF probe has to be designed carefully. Within our experiments, it is observed that the probe works well in terms of reliability and stability, when using the size $20 \times 20\text{mm}^2$ of each PVDF channel, the size like a fingertip area of Chinese physician touching the wrist pulse.

The PVDF generates electricity when pressed; but the output power of PVDF is lower than 1mV in amplitude. Additionally, the breathing, speaking, or wrist moving will bring noise that interferes the reliability and stability of PVDF. To address this problem, wee design an analog signal conditioning circuit which extracts raw wrist-pulse signals and feeds them to the MCU's ADC for further processing. Fig.4 illustrates an amplifier. The amplifier scheme is self-contained and then will not be explained because of the page limit.

3.2 A/D Conversion

We use MSP430 microcontroller and its built-in 12-bit ADC channel to receive the signal from the probe. The conversion is completed with $V_{out} = 4096(V_{in} - V_{-})/(V_{+} - V_{-})$, and the reference voltages are set with $V_{+} = 2.5\text{V}$ and $V_{-} = 0\text{V}$. By the single-repeat mode with SHT0_8 of MSP430, the sampling process of a single ADC channel consumes $T_{samp} = T_{ADC} \times 4 \times 64$ where T_{ADC} is the cycle of A/D and equals 200ns. We know that for MSP430 the synchronization time T_{sync} and the conversion time T_{conv} are one cycle and 13 cycles, respectively. Therefore the total

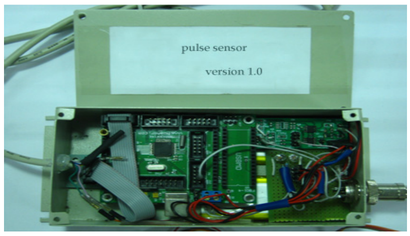

Figure 5: The prototype encapsulation

A/D conversion needs $T_{A/D} = T_{samp} + T_{sync} + T_{conv} = 54\mu\text{s}$, and the ADC frequency can achieve $1/T_{A/D} = 18.5\text{kHz}$, higher than 1kHz required by the TCM physicians.

3.3 Encapsulation

In order to facilitate the use of our system, we encapsulate the acquisition circuits, the MCU module, and two communication modules (RS232 and Bluetooth) within a box which connects the probe with a shielded wire. Fig.5 shows the encapsulation of the pulse-sensing system without the probe. The serial interface from the MCU is implemented with a serial-USB cable which can be plugged to the PC's USB port. Note that we have only implemented the wrist-pulse data transmission to the PC through the RS232 interface, even though a Bluetooth module has been embedded within the prototype; in our future work, we will focus on implementing the communication between the pulse-sensing system and the mobile phone by using the Bluetooth technology.

4. THE CIRRHOSIS DIAGNOSIS

4.1 Pulse Data Collection And Pre-processing

In this paper, pulse signals of radial artery are collected with 1000Hz by the sensor described previously. The serial port of PC reads the data form MCU. Labivew is used to design the graph user interface(GUI). Through the GUI, we can configure the asynchronous serial parameters, such as baud rate and data bits. The GUI can also display the pulse wave. Before collecting the data, all subjects take a rest of 10 minutes for keeping stable heart rate. The duration time of measuring is 20 seconds. Finally, the pulse data is stored locally.

During the acquisition, the pulse signals can be easily contaminated by subject's respiration and artifact motion, because pulse signal is a kind of weak physiological signal. Therefore, preprocessing is necessary before further process. In our system, the procedure of data preprocessing contains noise removal and baseline wander correction. The upper panel of Fig.6 illustrates the raw pulse signals.

4.1.1 Signal Denoising

We use the discrete wavelet transform (DWT) method to denoise physiological signals, which is often used in real-time applications. It can effectively remove noise and at the same time, maintain the important information involved within the signals. The signal denosing based on DWT usually has three steps: the signal decomposition, the threshold determination, and the signal reconstruction. Firstly, we employ the DWT to transform the raw pulse data into the high-frequency and low-frequency coefficients. The DWT

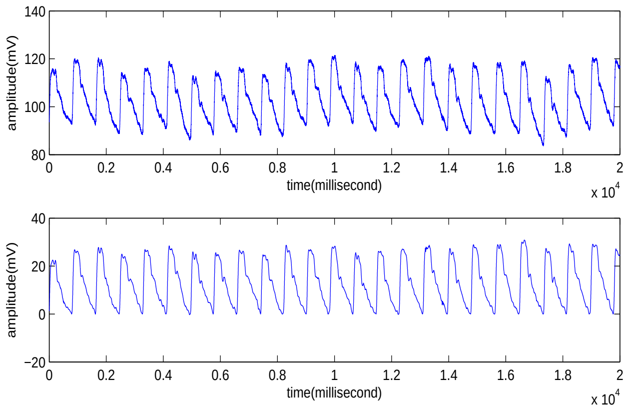

Figure 6: The raw pulse signals (top) and the preprocessed signals (bottom)

procedure can be modeled with

$$\begin{aligned} c^{j-1} &= \mathrm{Con}(\mathrm{c^j} * \bar{\mathrm{h}}^*) \\ d^{j-1} &= \mathrm{Con}(\mathrm{c^j} * \bar{\mathrm{g}}^*) \end{aligned} \qquad (1)$$

where, the $c^{j-1}$is the low frequency data(Dc), d^{j-1} is the detailed information when c^{j-1} approaches to c^j, Con() is the convolution operation, and h and g are the Low-pass and High-pass filters, respectively.

We use "db6" wavelet to perform a DWT with six-level decomposition because "db6" wavelet function is similar, in shape, to the pulse signals of radial artery.

For effectively determining the threshold for denoising the raw signals, Eq.(2) is used, and the experimental results show that such thresholding can achieve a higher signal-to-noise ratio (SNR) than the sqtwolog method.

$$\mathrm{Th_i} = \frac{\sigma\sqrt{2\log \mathrm{N}}}{\log(\mathrm{i}+1)} \qquad (2)$$

where N is the signal length, $\mathrm{Th_i}$ stands for the threshold at level i and σ is the median of the detailed coefficients at all levels of signal decompositions.

$$\sigma = \frac{|\mathrm{median(detail)}|}{0.674} \qquad (3)$$

Once the threshold value has been calculated, we can apply the soft thresholding policy because the wavelet coefficients generated by the soft thresholding is of good continuity. For each wavelet transform coefficient $\mathrm{W_{ij}}$ and threshold $\mathrm{Th_i}$, the soft thresholded value can be expressed with

$$\begin{aligned} \mathrm{W^t_{ij}} = \mathrm{sign}(\mathrm{W_{ij}})(|\mathrm{W_{ij}}| - \mathrm{Th_i}) \text{ if } |\mathrm{W_{ij}}| \geq \mathrm{Th_i} \\ \mathrm{W^t_{ij}} = 0 \text{ if } |\mathrm{W_{ij}}| < \mathrm{Th_i} \end{aligned} \qquad (4)$$

where sign$(\cdot)$ is the sign-function and $\mathrm{W^t_{ij}}$ represents the new value of the j-th wavelet coefficient at the i-th level obtained after thresholding. The threshold $\mathrm{Th_i}$ was applied only to the detailed coefficients.

4.1.2 Baseline Wander Removal

Some researchers have proposed various solutions to correct the baseline wander in physiological signals. Among these methods, linear interpolation is the simplest one. But, linear interpolation suffers from a disadvantage: it may introduce more distortion, compared with the cubic spline interpolation[19]. Techniques like wavelet filters and adaptive filters need lots of computation and then are time-consuming. Here we make a tradeoff between time and efficiency, and we choose the cubic spline interpolation to remove the baseline wander. The bottom figure in Fig.6 illustrates the denoised pulse signals without the baseline wander. Next we will present the detailed procedure of removing the baseline wander.

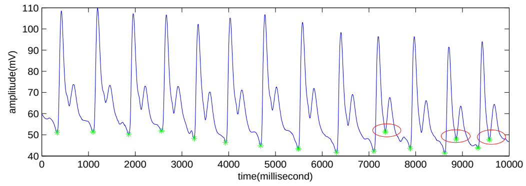

Figure 7: The points of false identification which should be filtered out

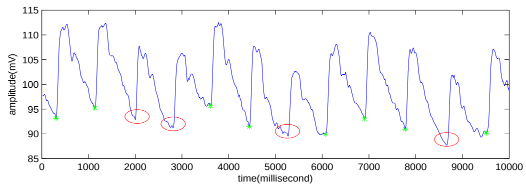

Figure 8: The points of false identification which should be identified

Before correcting baseline wander, the single-period of pulse signals should be obtained at first. We obtain every period using a heuristic method as follows.

Step 1: Find the global maximum and the global minimum values from pulse signals. After that, we can empirically get a threshold of (maximum-minimum)/3. If we set the threshold too small, then some points can be found but they are not the onsets of the period, as shown by the points with red circle in Fig.7. If we set the threshold too large, then some onsets of the period can be omitted, as shown in Fig.8. That is why we use the threshold of (maximum-minimum)/3 which can almost achieve 100% accuracy.

Step 2: Find all local maximum and minimum values from the pulse waveform and save them in an array in order. If the difference between two adjacent local maximum and local minimum is greater than the threshold, we label the local minimum as the onset of a period and save it in an array (the local maximum is saved in another array as the amplitude of the percussion wave of the corresponding period).

4.2 Feature Extraction

Generally there are a few feature extraction methods which are widely used, covering, say, the time domain feature extraction [24], the frequency domain feature extraction [25], the time-frequency feature extraction [21], the curve fitting [4, 3], and the dimension reduction techniques(DRT) [9, 20].

Even though being simple, the time domain feature extraction has some disadvantages. Fig.9 illustrates one period of pulse signals with some of time-domain parameters marked by $\mathrm{t_i}$ (i=1 to 3) and $\mathrm{h_j}$ (j=1 to 4). Practitioners believe that these parameters are of physiological significance. For example, h1 can reflect the left ventricular ejection function and vascular compliance. Some researchers employ these time-domain features as the inputs to the classifier. But tidal wave or dicrotic wave is very weak sometimes, and

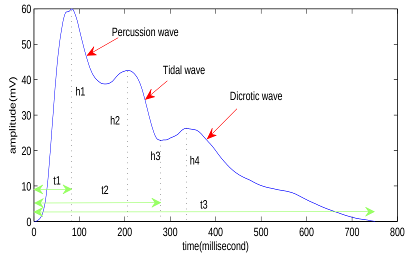

Figure 9: a period of pulse waveform

then the sensor cannot detect such waves; therefore, one period of pulse waveform may not have tidal wave or dicrotic wave. Without them, we cannot accurately identify these points that will affect the classification performance. Without considering the time complexity, the time-frequency feature extraction is feasible and can obtain good recognition results. The curve fitting may over-fit the data. The key idea of DRT is to represent the high-dimensional raw data on an intrinsic low dimensional space, but it works with more complexity.

In our study, we need to find a simple and time-efficient method, which is highly needed by mobile applications. We use the binning method, a new kind of method to extract the features. It can smooth the data and we can determine the number of features easily. The binning method needs two parameters: the window size s and the step length l, and it works as follows. (1) Perform summation on the data in the current window, (2) move the start point for current window by step length l, and (3) repeat steps (1) and (2) until the window reaches to the end of the period. We then take the sum data of all windows as features.

It is noticeable that before executing the binning method, each period is set with the same length. But from the above figures, we find that the signal lengths over subjects are different. Even for the same subject, the lengths from period to period are different. The average of heart rate for adults is about 75 beats per minute, i.e., the duration of a single heartbeat is 0.8 second in average. Here we therefore set the length of each period to be 800. We observe that the amplitude of the last quarter of the period always approaches to zero, contributing less to the classification. So we adjust those periods whose lengths are less than 800 by appending 0 at the end, and truncate the extra part for those with the length of more than 800.

4.3 Classification

The extracted features are used as inputs to the classifier for further classification. The classification aims to telling healthy persons from patients of cirrhosis. Now, NN[9], SVM[21, 4, 16], Neural Network[18], and FCM[3] are the mostly-adopted methods. In this paper, the k-nearest neighbor(KNN) algorithm is adopted for classification.

The KNN method is a simple-but-effective method for classification. It classifies an object based on the majority voting policy. For a test sample, its k nearest neighbors are retrieved, where k is a user-defined constant, and those neighbors forms a neighborhood of the test sample. Finally the sample can be classified by assigning the label which is most frequent among the k nearest neighbors. In this paper we use Euclidean distance as the distance metric in classification. Given a test example x_i and a training example x_j, y_i and y_j represent the corresponding feature vector, respectively. The distance between y_i and y_j is computed as

$$\mathrm{D}(\mathrm{y_i}, \mathrm{y_j}) = \|\mathrm{y_i} - \mathrm{y_j}\| \tag{5}$$

Table 1: The comparison of performance. AH is the accuracy for healthy subjects, AC the accuracy for cirrhosis subjects, AO the overall accuracy, and DP the Doppler parameters method.

Method	Parameters	AH (%)	AC (%)	AO (%)
Binning	size=40	95	72.72	87.09
	length=40			
	k=3			
KPCA	m=20	90	72.72	83.07
	β=10000			
DP	RT	90	63.63	80.64
	SW			

5. EXPERIMENTS

The dataset collected in our experiments contains a total of 84 subjects—there are 56 healthy persons and 28 cirrhosis patients. We divide the pulse dataset into two groups: a training set and a testing set. We assigned individuals randomly to test and training data. There were 36 healthy and 17 cirrhosis patients in the training data and 20 healthy and 11 cirrhosis patients in the test data.

In experiments, use the data only for the "Guan" position to perform classification due to the following reasons. According to the theory of TCM ([6, 8]), the pulse-taking positions are related to the body organs, and the pulse at the "Guan" position is associated with the cirrhosis.

Firstly the method presented in Section 4.1 is used to the collected data, and then we get the single-period waveform with the length of 800. For each sample, we use one period data to extract features and carry out the classification. In this paper, we use a total number of five periods. Thus, we get five class labels and the final class label is the one which is most frequent among the five labels. When we adjust the window size, the step length, and the k value of KNN, we find that if k is equal to 3, the window size to 40, and the step length to 40, we achieved the best classification performance with an accuracy of 95% for healthy subjects (5% false positive rate), the accuracy of 72.72% for the cirrhosis subjects (27.28% false negative rate), and overall rate of correct classification of 87.09%.

In our experiments, we also carry out the KPCA method [9] and the Doppler Parameters method [21] in features extraction before the classification starts. The results are listed in Tab.1, and we can see that the features extracted by binning method used in this paper leads to best classification results. Note that the length of a single period is set to be 800. If we use 20 dimensions to represent the period, some important features may be lost. So the KPCA method is unsatisfied. The SW feature of the Doppler Parameters method cannot accurately represent the width of the percussion wave that reaches to 1/2 height, if the tidal wave happens early.

6. CONCLUSIONS AND FUTURE WORK

This study has proposed a wrist-pulse sensing system containing two parts: a three-channel PVDF sensor (called probe) to capture the wrist pulse signals, and a MSP430-based module used to receive the pulse information and transmit it to external processing module. Based on the proposed system we have implemented the cirrhosis identification scheme. The experimental results demonstrate the accuracy and efficiency of our system. In future we will design more precise wrist-pulse sensor to meet some more complicated pulse diagnosis, and we will implement the communication module based on the Bluetooth interface, by which a commercial-off-the-shelf mobile phone can serve as the data processing device, making the system more suitable to mobile healthcare applications.

7. ACKNOWLEDGMENT

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