Web-based Remote Human Pulse Monitoring System with Intelligent Data Analysis for Home Healthcare

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Abstract —**Many studies had indicated that applying intelligent systems with physiology signal monitoring for e-health care is a current developing trend. A physiology signal monitoring system can help medical staffs to monitor and analyze human's physiology signal effectively, such that they can not only monitor the patients' physiology states immediately, but also reduce medical cost and save a lot of time of patients to visit hospital's doctors. Therefore, the study employed system on chip (SOC) techniques to develop an embedded human pulse monitoring system with intelligent data analysis mechanism for disease detection and long-term health care, which can be applied to monitor and analyze human's pulse signal in daily life. Meanwhile, the proposed system also developed a friendly web-based interface that is convenient to the observation of immediate human physiological signals. Moreover, this study also proposes an intelligent data analysis scheme based on the modified cosine similarity measure to diagnose abnormal human pulses for exploring potential chronic diseases. Therefore, the proposed system provides benefits in terms of aiding long-distance medical treatment, exploring trends of potential chronic diseases, and urgent situation informing for sudden diseases.**

Keywords—**pulse physiology signal monitoring system, embedded system, e-health care, sequence data analysis**

I. INTRODUCTION

With progress of medical technologies and development of newer and better medicines, many countries are gradually coming into geriatric societies due to rapid growth of the aging population, such that the requirement of home health monitoring has been increasingly raised for securing independent lives of elder or aged patients [1]. Particularly, advancements of physiological sensors, wireless communications, and information technologies have resulted in the rapid development of various wellness or disease monitoring systems, which enable extended independent living at home and improvement of quality of life for individuals [2]. Many studies [2] [3][4] had indicated that monitoring human physiological information in real-life conditions is especially useful in management of chronic disorders or healthcare problems. Importantly, performing long-term monitoring process is helpful to provide follow-up data to observe long-term trends in the wellness or health status.

In the past years, many researches paid much attention on developing long-term health-care monitoring systems [5][6], which are required to be compact, lightweight, low power consumption, low-cost and comfortable to be used at anytime. Furthermore, they must be able to detect physiological signals reliably and stably in various disturbances. Most of the researches for health-care monitoring in out-of-hospital environment have concentrated on health monitoring at home [2][3][5][6][7][8]. Furthermore, there are research trends towards developing wearable physiological monitoring systems that can measure various bio-signals and provide healthcare services to user using e-Health technology [7][8]. Moreover, the concept of remote monitoring vital signal by web-based interface [9][10], which is helpful to transmit immediate physiological parameters to physicians who are capable of interpreting the measurements for individuals, is also a key issue for physiological signal monitoring systems. It is not only convenient to individuals who are actively willing to receive feedback regarding his/her wellness or disease status and to participate in his/her own care, but also provides the benefit of distance treatment.

Among human vital signals, assessment of human pulse has long been a research area of interest in the physiology field because the situations of human pulse reflect many health states [11][12]. Human pulse is the rate at which human heart beats. Therefore, human pulse is usually called heart rate, which is the number of times your heart beats each minute. However, the rhythm and strength of the heartbeat can also be noted, as well as whether the blood vessel feels hard or soft. Changes in your heart rate or rhythm, a weak pulse, or a hard blood vessel may be caused by heart disease or another problem.

Based on the importance of monitoring human pulse, the study aimed to develop a novel web-based remote human pulse monitoring system with intelligent data analysis based on physiological sensor, SOC (system on chip), wireless communication, World Wide Web, and intelligent data analysis technologies, for wellness monitoring and homecare. The main emphasis was on building a handheld SOC-based human pulse monitoring system, which integrated with wired home Internet network to transmit physiological signals to a remote physiological information database through wireless communication interface on SOC platform. The proposed system also developed a friendly web-based interface that is convenient to the observation of immediate human

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physiological signals to support distance treatment. In addition, this study also proposes an intelligent data analysis scheme based on the modified cosine similarity measure to identify the similarities between any two human pulse sequences. The proposed scheme is helpful to diagnose abnormal human pulses for exploring potential chronic diseases.

II. SYSTEM DESIGN

This section introduces the system design based on physiological sensor, signal preprocessing, embedded system, wireless communication, and World Wide Web technologies.

A.. System Architecture

This study presents a web-based remote human pulse monitoring system which is composed of three parts including the pulse signal measuring module, the ARM embedded system platform and the remote server. Figure 1 presents the system architecture of the proposed system. The pulse signal measuring module aims to sense the human pulse signals via the piezoelectric sensor and to perform the signal preprocessing process for filtering out noisy signal. To transfer human pulse signals to the embedded system, the analog human pulse signals are first transferred into digital signals by analog-digital converter, and then transmit to the embedded system through serial transmission device under a predefined baud rate. When the collected human pulse data meet the predetermined amount, the embedded system transmits the human pulse data to the remote server by wireless communication. Finally, the remote server stores the sensing human pulse signals into human physiology database as well as shows the physiology signals to medical personnel through web interface. The web-based interface provides benefit in terms of on-line remote medical diagnosis for home-health care. Furthermore, this study presents an intelligent data analysis scheme based on a symbolic-based hamming distance similarity measure to detect abnormal human pulse for home-health care.

B. The Employed Scheme for Computing the Human Pulse Rate

Since the human pulse signal is similar to the electrocardiogram (ECG) signal, the real-time QRS detection algorithm [13] was applied to compute the human pulse rate in this study. The algorithm can detect the position of R-wave, and then use the interval time between any two R-waves to compute the human pulse rate. Figure 2 illustrates the detailed procedures of estimating human pulse rate. The computing procedures include differentiating, squaring, moving-window integration, filtering out the signal elements that their voltage levels are 2/3 low than the highest voltage level, computing interval time between any two R-waves, and estimating human pulse rate.

Next, this study gives an example to explain how to estimate human pulse rate by the employed real-time QRS detection algorithm. First, Fig. 3 shows the original pulse signal obtained from the signal preprocessing circuit. Based on the real-time QRS detection algorithm, the original human pulse signal must be first differentiated to obtain the slope information. Figure 4 depicts the differentiated result of the human pulse signal. After performing differentiation operation, the human pulse signal is squared to emphasize the slope of the R-wave. Figure 5 shows the human pulse signal after performing squaring operation. The next process is to perform the moving-window integration operation. The moving-window integration aims to filter out the noise near the R-wave. Figure 6 reveals the human pulse signal after performing moving-window integration operation. To preserve useful signal elements for computing human pulse rate, the other signal elements should be filtered out excluding R-wave. Figure 7 shows the human pulse signal that filters out the signal elements that their voltage levels are 2/3 low than the highest voltage level. Finally, the human pulse rate can be computed according to the time interval between any two R-waves. The human pulse rate can be estimated by the following formula:

$$f_h = \frac{1}{td} \times 60 \tag{1}$$

where f_h is the human pulse rate, and t_d is the interval time between any two turning points.

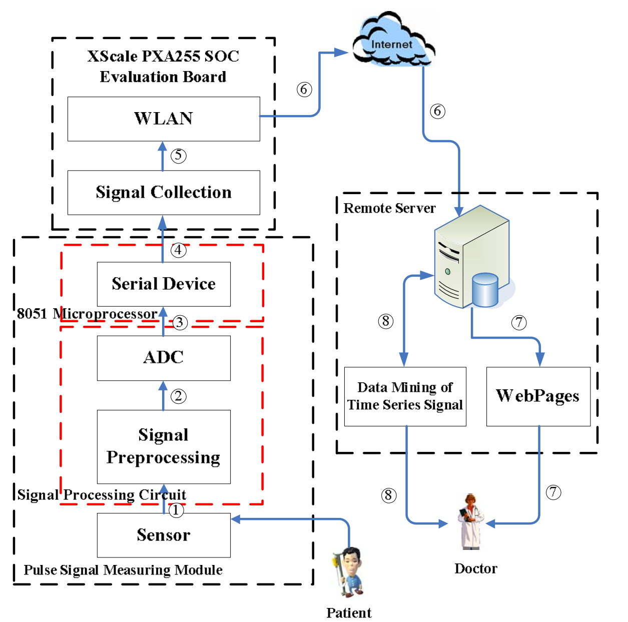

Fig. 1. System architecture of the proposed web-based remote human pulse monitoring system

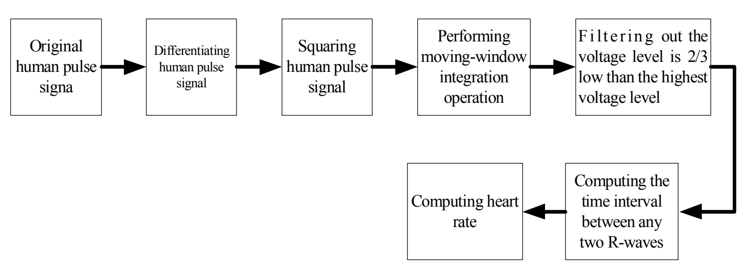

Fig. 2. The computing procedure of human pulse rate

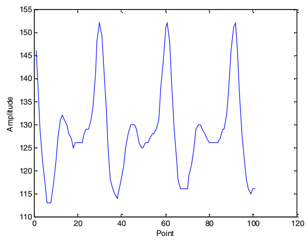

Fig. 3. The original human pulse signal

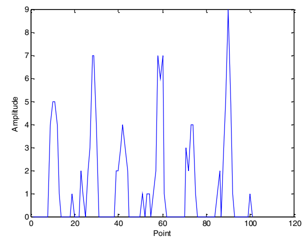

Fig. 4. The human pulse signal after performing differentiation operation

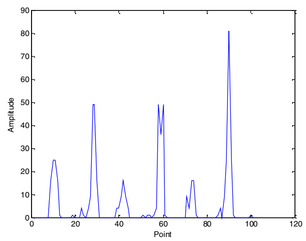

Fig. 5. The human pulse signal after performing square operation

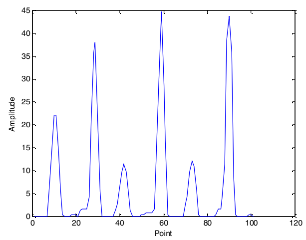

Fig. 6. The human pulse signal after performing moving-window integration operation

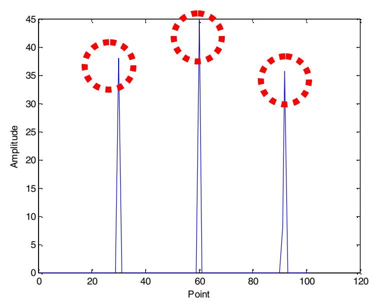

Fig. 7. The human pulse signal that filters out the signal that its voltage level is 2/3 low than the highest voltage level

C. The Proposed Modified Cosine Similarity Measure for Identifying Abnormal Human Pulse Sequence

First, in order to identify abnormal human pulse sequence using the proposed modified cosine similarity measure, the symbolic transformation was used to represent a human pulse signal in this study. The major concept is to transfer the human pulse signal with numerical data type into the human pulse signal with symbolic data type by assigning corresponding symbol to each sampling human pulse signal. The primary advantage of the symbolic transformation is to reduce the computational complexity of identifying abnormal human pulse sequence, but this transformation could lose the original character of human pulse signal. Therefore, this study employs the slope transformation to identify the original features of human pulse signal before performing the symbolic transformation. After transforming the human pulse signal into the symbolic data sequence, the proposed modified cosine similarity measure is applied to estimate the similarity degree between any two symbolic sequences for identifying abnormal human pulse sequences. Next, the slope and symbolic transformations are detailed as follows:

(A) Slope transformation

In order to identify the features of human pulse signal for transferring an original human pulse signal into symbolic data sequence, the slope transformation is first operated before performing symbolic transformation in the study. Suppose that the sequence $S=\{s_1,s_2,s_3,\ldots,s_i,\ldots,s_m\}$ represents m sampling human pulse signal points, and the sequence $T=\{t_1,t_2,t_3,\ldots,t_i,\ldots,t_m\}$ is each corresponding sampling time. The slope transformation can be performed by the following mathematical formula:

$$S'=\frac{s_{i+1}-s_i}{t_{i+1}-t_i},\quad 1\le i\le m-1 \tag{2}$$

where $S'=\{s'_1,s'_2,s'_3,\ldots,s'_i,\ldots,s'_{m-1}\}$ stands for the transformed human pulse sequence, s_i is the i^{th} sampling human pulse signal point, t_i is the corresponding sampling time of the i^{th} human pulse signal point, and m represents the total number of sampling human pulse signal points.

(B) Symbolic transformation

After performing the slope transformation, the varied statuses of a human pulse signal are successfully extracted for symbolic transformation. There are two factors that need to be considered when performing symbolic transformation: one is how many symbolic characters should be used, and another is how much information of the human pulse signal could be lost under using limited symbolic characters for symbolic transformation. Actually, these two considerations are trade-off issue. More symbolic characters have to be used if more complete human pulse information need to be preserved, but such symbolic transformation will increase the computational complexity of identifying abnormal human pulse signals. Conversely, using less symbolic characters will lose some human pulse information, but it can reduce the computational complexity of identifying abnormal human pulse signals. To make all sampling points of human pulse signal that have performed the slope transformation becoming comparative sequences to each other, the z-score normalization must be first conducted before performing the symbolic transformation. The z-score normalization is formulated as follows:

$$s''_i=\frac{s'_i-\overline{s}'}{\sigma'} \tag{3}$$

where s''_i stands for the i^{th} human pulse signal with z-score normalization, s'_i is the i^{th} human pulse signal with angular transformation, $\overline{s}'$ is the mean of the human pulse signals with angular transformation, and σ' is the standard deviation of the human pulse signals with angular transformation.

The human pulse sequence that performs the z-score normalization has three properties: the mean is zero, the standard deviation is one, and all human pulse data form a normal distribution. TABLE I displays the cut-point of the normal distribution based on various transformation symbols. In

TABLE I, the cut-points partition the normal distribution function as several non-overlapped areas with equal probability. For example, two cut-points –0.43 and 0.43 partition the normal distribution function into three non-overlapped areas, and each area has 1/3 occurrence probability.

TABLE I
THE CUT-POINT OF THE NORMAL DISTRIBUTION BASED ON VARIOUS TRANSFERRED SYMBOLS

The number of transformation symbols	Cut-point
3	(-0.43, 0.43)
4	(-0.67, 0, 0.67)
5	(-0.84, -0.25, 0.25, 0.84)
6	(-0.97, -0.43, 0, 0.43, 0.97)
7	(-1.07, -0.57, -0.18, 0.18, -0.57, -1.07)
8	(-1.15, -0.67, -0.32, -0.14, 0.14, 0.32, 0.67, 1.15)
9	(-1.22, -0.76, -0.43, -0.14, 0.14, 0.43, 0.76, 1.22)
10	(-1.28, -0.84, -0.52, -0.25, 0, 0.25, 0.52, 0.84, 1.28)

(C) The proposed modified cosine similarity measure for identifying abnormal human pulse signal

To identify abnormal human pulse signal, this study employs the cosine similarity measure to compute the similarity degree between any two human pulse sequences. Suppose that the union symbols' set obtained from the human pulse sequence P_a and the human pulse sequence P_b contains a total of k symbolic terms. The similarity degree between two human pulse sequences measured by the cosine measure can be formulated as

$$Sim(P_a, P_b) = \frac{\sum_{i=1}^{k} s_{ai} s_{bi}}{\sqrt{\sum_{i=1}^{k} s_{ai}^2 \sum_{i=1}^{k} s_{bi}^2}} \tag{4}$$

where $P_a = (s_{a1}, s_{a2}, ..., s_{ai}, ..., s_{ak})$ and $P_b = (s_{b1}, s_{b2}, ..., s_{bi}, ..., s_{bk})$ represent respectively the symbol vectors of the human pulse sequence P_a and the human pulse sequence P_b, s_{ai} and s_{bi} stand for the symbol weights of the *ith* symbol in the human pulse sequence P_a and the human pulse sequence P_b, respectively.

In Eq. (4), the corresponding symbol weight in the symbol vector is computed based on the symbol frequency that appears in a human pulse sequence. However, the cosine similarity measure cannot identify the similarity degree between any two human pulse sequences well, because it cannot completely reveal a human pulse symbolic semantics. For example, the similarity degree of the human pulse sequence "ABCD" and "DCBA" measured by cosine measure is equal to 1 since both the human pulse sequences include the same set of symbolic terms. This similarity degree evaluated by cosine measure implies that both human pulse sequences are completely identical in terms of semantics, but they have completely different meanings from the perspective of human pulse signal. In other words, the human pulse symbol that appears at different positions represents different meaning.

To consider a symbol's position for promoting the accuracy when identifying abnormal human pulse sequences, the proposed hamming distance was applied to modify the cosine measure for measuring the similarity degree between two human pulse sequences with increased precision. The proposed hamming distance for both the human pulse sequences can be computed using the following formula:

$$H_{P_a, P_b} = \sum_{i=1}^{m} \left| L(s_{ai}) - L(s_{bi}) \right| \tag{5}$$

where $L(s_{ai})$ and $L(s_{bi})$ represents respectively the transformed location index values of the *ith* symbol that appears simultaneously in the symbol sequences of both the human pulse sequence P_a and human pulse sequence P_b, m is the total number of symbols that appear simetaneously in the symbol sequences of both the human pulse sequence P_a and the human pulse sequence P_b.

To consider both similarity degree and symbol sequence semantics simultaneously when identifying abnormal human pulse sequences, the modified cosine measure is expressed as

$$Msim(P_a, P_b) = \left(1 - \frac{H_{P_a, P_b}}{Max(H)}\right) \times Sim(P_a, P_b) \tag{6}$$

where $Max(H)$ represents the maximum hamming distance among the human pulse sequence P_a with all identifying human pulse sequences.

Next, this study gives an example to explain how to compute the hamming distance between two human pulse sequences. Suppose that the human pulse sequence P_a contains four symbolic terms after performing symbolic transformation, and the symbolic term set of the human pulse sequence P_a is represented as $P_a = \{s_1, s_2, s_3, s_4\}$. To compute hamming distance, term set P_a must be transformed into a location vector based on the order in which symbols appear. For example, the transformed location vector of symbolic term set P_a is represented as $L(P_a) = (1,2,3,4)$ for the corresponding symbolic term set $P_a = \{s_1, s_2, s_3, s_4\}$. Moreover, suppose that the symbolic term sets of another two human pulse sequences P_b and P_c are $P_b = \{s_1, s_3, s_5\}$ and $P_c = \{s_1, s_5, s_3\}$, respectively. Similarly, the transformed location vectors for both P_b and P_c are $L(P_b) = (1,2,3)$ for symbolic term sets $P_b = \{s_1, s_3, s_5\}$, as well as $L(P_c) = (1,2,3)$ for symbolic term set $P_c = \{s_1, s_5, s_3\}$. Therefore, the hamming distances between the human pulse sequence P_a with the news events P_b and P_c can be computed as

$$H_{P_a, P_b} = |1-1| + |3-2| = 1$$

$$H_{P_a,P_c} = |1-1| + |3-3| = 0$$

III. Experiments

Currently, the proposed web-based remote human pulse monitoring system was implemented on an embedded system with Linux operation system. The Apache web server, PHP language, and MySQL database were employed to develop the server side system. This section reveals the implemented web-based remote human pulse monitoring system and demonstrates the performance of the proposed modified cosine similarity for exploring abnormal human pulses.

A. The Implemented Web-based Remote Human Pulse Monitoring

Figure 8 shows the implemented web-based remote human pulse monitoring system, which includes the pulse transducer piezoelectric sensor for sensing human pulse signal, signal preprocessing circuit for filtering our noisy signal and amplifying weak human pulse, ARM embedded system with Linux operation system for transmitting human pulse into web server by wireless networks, web server with human physiology database for collecting immediate human pulse signal, oscilloscope for verifying the quality of sensing human pulse signal, and power supply. Using this system, medical staffs can directly observe human pulse signal by web browser from any place. This provides benefits in terms of long-distance medical treatment, exploring trends of potential chronic diseases, and urgent situation informing for sudden diseases. To verify the implemented system can correctly measure human pulse signals, Fig. 9 simultaneously shows a human pulse signal on both the web interface and oscilloscope. Except displaying immediate human pulse signal, the web interface can also display the corresponding heart rate. This study confirmed that the human pulse signal displayed on the oscilloscope is the same with the human pulse signal displayed on the web browser.

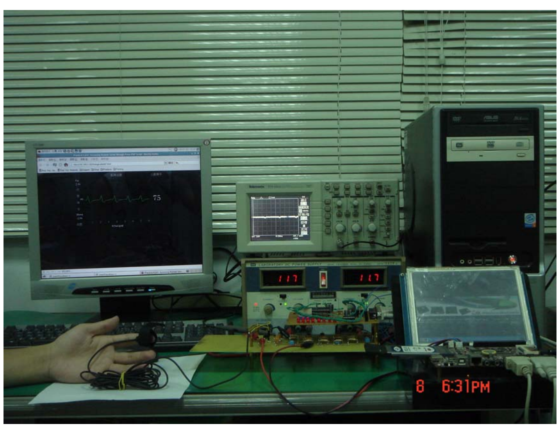

Fig. 8. The implemented web-based remote human pulse monitoring system

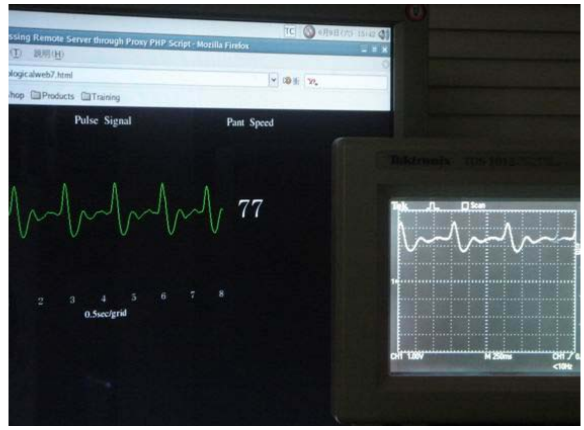

Fig. 9. The human pulse signal simultaneously displayed on both the web interface and oscilloscope

B. Exploring Abnormal Human Pulse by the Proposed Modified Cosine Similarity Measure

To demonstrate whether the proposed modified cosine similarity measure can correctly explore abnormal human pulses, this study measured five actual human pulse signals from five different persons to compare their similarities to each other by the cosine similarity measure and the proposed modified cosine similarity measure. This experiment aims to demonstrate that the proposed modified cosine similarity measure can correctly explore two most similar human pulse patterns to each other from a human pulse physiological database. This will be helpful to judge whether a sensing human pulse is similar to any abnormal human pulses stored in human pulse physiological database. Fig. 10 shows five human pulse signals sensed from five different persons. To compute similarities between any two human pulses, the symbolic transformation must be first performed. This study adopted ten symbolic characters to represent the original human pulse as symbolic data sequence by the proposed symbolic transformation process. TABLE II shows the result of symbolic transformation. TABLE III and IV show the similarities measured by the cosine measure and the proposed modified cosine measure, respectively. The experimental result listed in TABLE III indicates that the human pulse 1 (i.e. data 1) is most similar to the human pulse 4 (i.e. data 4). However, Fig. 10 obviously shows that the human pulse 1 is most similar to the human pulse 3 (i.e. data 3) in this case, not the human pulse 4. The experimental result listed in TABLE IV confirms that the proposed modified cosine similarity measure can correctly identify this problem because the position semantics of human pulse sequence and symbolic appearance frequency are simultaneously considered.

IV. Conclusions

This study presents a Web-based remote human pulse monitoring system with intelligent data analysis based on physiological sensor, SOC (system on chip), wireless communication, World Wide Web, and intelligent data analysis technologies for home healthcare in daily lives. The proposed system not only can correctly sense and transmit human pulse signals to human physiological database in a server side, but also provide a friendly web-based interface that is convenient to the observation of immediate human physiological signals and heart rate to support distance treatment in a client side. In addition, this study also presents a modified cosine similarity measure, which can identify abnormal human pulse sequences, to support exploring potential chronic diseases. More importantly, the proposed system was successfully implemented by embedded system technology. This provides benefits in terms of developing compact, lightweight, low-cost and hand-held physiology monitoring system.

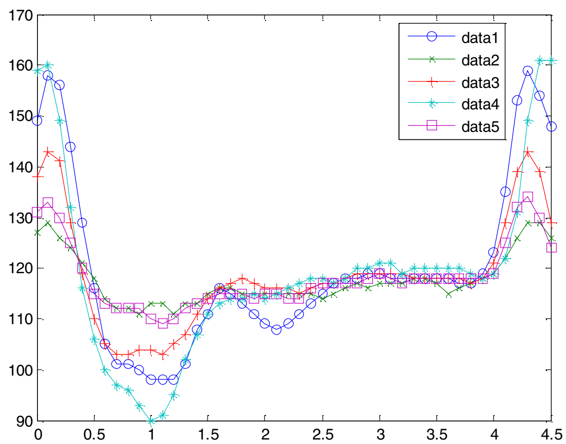

Fig. 10. T The human pulse signals sensed from five persons

TABLE II. THE SYMBOLIC TRANSFORMATION RESULTS OF THE HUMAN PULSE DISPLAYED IN FIG. 11

Elements	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Data1	A	G	J	J	J	J	H	E	F	G	E	E	C	B	C	B	F	G	G	G	F	E
Data2	B	J	I	J	J	J	I	E	H	B	E	I	B	E	B	C	E	H	E	E	E	E
Data3	A	G	J	J	J	I	G	E	D	E	F	C	C	B	C	C	D	D	F	F	E	E
Data4	E	J	J	J	J	I	H	F	H	H	E	C	B	B	C	D	E	F	E	F	E	E
Data5	B	I	J	J	J	H	G	E	E	H	G	D	B	D	D	D	E	E	G	D	E	G
Elements	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**
Data1	D	D	D	D	E	E	E	E	F	E	E	E	E	E	F	E	D	C	A	A	B	I
Data2	E	E	H	C	C	C	H	C	E	E	C	E	H	I	C	C	C	C	A	A	A	E
Data3	F	D	D	E	D	D	E	E	E	E	F	E	E	E	E	F	D	C	A	A	B	I
Data4	E	E	F	F	E	D	F	E	F	G	E	F	F	F	F	F	F	E	D	A	A	A
Data5	E	B	D	E	E	E	D	D	G	G	D	E	E	E	E	E	E	D	A	A	B	J

TABLE III. THE SIMILARITIES MEASURED BY THE COSINE MEASURE

Data(R) \ Data	1	2	3	4	5
1	1	0.44794	0.77683	0.79644	0.62921
2	0.44794	1	0.39682	0.43306	0.43049
3	0.77683	0.39682	1	0.69901	0.47775
4	0.79644	0.43306	0.69901	1	0.53881
5	0.62921	0.43049	0.47775	0.53881	1

TABLE IV. THE SIMILARITIES MEASURED BY THE MODIFIED COSINE MEASURE

Data(R) \ Data	1	2	3	4	5
1	1	0.14931	0.50494	0.44601	0.35393
2	0.14931	1	0.17637	0.21653	0.19133
3	0.50494	0.17637	1	0.2796	0.19906
4	0.44601	0.21653	0.2796	1	0.40411
5	0.35393	0.19133	0.19906	0.40411	1

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