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INTELLIGENT HEART RATE MONITORING USING EMPIRICAL ALGORITHM AND DYNAMIC TIME WRAPPING

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Abstract. *This paper lays emphasis on heartbeat monitoring. The polyvinylidene difluoride (PVDF) material is used as the sensor for signal acquisition. There are two crucial subjects in this paper that shall be solved for heart rate calculation. First, the difference in signal amplitude shall be overcome (each analyte has a different heartbeat amplitude or intensity), so that the algorithm can calculate the heart rate effectively. Secondly, the difference in signal frequency or cycle is overcome (each analyte has a different heart rate or cycle), so that the accuracy of calculated heart rate is increased. Finally, the signal acquisition makes noise, which influences the calculation of heartbeat. The signal shall be preprocessed to remove the noise. Added to this, the sensor is placed in different positions, and the algorithm shall identify the signal as heartbeat signal or other signals, which contributes to calculating the heart rate rapidly. Our algorithm can calculate the heart rate effectively when the sensor is placed in different positions (chest and wrist) and overcome the effect of different signal cycle lengths.*
Keywords: DTW, Empirical algorithm, Heart rate monitoring, PVDF

1. **Introduction.** In recent years, the heartbeat monitoring plays an important role in health care and fitness [1]. A highly correct measured data can provide doctors or experts with more information for decision on diagnosis or advice. The basic physiological signals, such as heart rate, pulse rate and respiratory rate, are extensively used to evaluate basic functions of normal persons. The common commercially available medical grade vital signs monitors in clinical medicine can implement timely and high precision multi-physiological information monitoring. In general cases, these medical appliances are very expensive and large sized, unlikely to be carried, so they may obstruct the practical application of home care. For the patients with cardiovascular chronic disease, the sustained heart rate or pulse rate monitoring is very important at any time, in any location. In order to implement physiological information monitoring of home care for patients, a portable and high precision wearable device is particularly required. The PVDF (polyvinylidene difluoride) is a sort of PVF2 compound, piezoelectric plastic material with uniform and solid structure. The piezoelectric characteristic has significant effect on measuring the physiological signals of human body, especially on cardiorespiratory signal measurement [2-4]. Besides good sensing function, the PVDF is characterized by thinness, light weight, flexibility and low cost. These favorable characteristics make it an ideal material for manufacturing wearable devices. This paper uses CM-01B [5], which is extensively used in the design of electronic stethoscope. It is a good electronic part for monitoring heart rate, pulse and respiratory rate. The heartbeat detection technique has progressed greatly in medicine or fitness. For example, the PPG (photoplethysmography) is extensively used

in wearable devices, because the PPG sensor has simple operating characteristic (as long as it is attached to skin) and low cost. Many major companies have used this technique in smart watches or bracelets for health monitoring.

This paper proposes combining empirical algorithm with dynamic time wrapping (DT-W) algorithm to increase the accuracy and reliability of heart rate monitoring. The empirical algorithm judges local peak value effectively based on peak detection in time domain. The DTW measures the similarity between two signal sequences, and it is usually used in speech recognition and handwriting recognition [6]. This algorithm can overcome the difference in signal frequency or cycle effectively. There is significant effect in the experiment.

The main contribution of this paper is that we propose an intelligent empirical algorithm integrated with DTW (dynamic time warping) to overcome the differences in signal amplitude and cycle. Our motivation is that this algorithm can be easily ported to embedded systems and applied not only on human beings but also animals. This paper is devoted to designing an algorithm that can support diversity application areas. Our design system will be applied to assisting the pig's surgery in monitoring vital sign. Hence, our proposed algorithm can be of benefit in the field of veterinary medicine. In addition, we investigate the household pets are becoming increasingly common in modern society and pet heart rate monitoring is a major issue for many owners.

The rest of this paper is organized as follows. Background knowledge and related work are presented in Section 2. The proposed algorithm and experimental evaluations are presented in Sections 3 and 4, respectively. Section 5 concludes the paper and offers suggestions for future studies.

2. **Related Works.** Electrocardiogram (ECG), photoplethysmography (PPG) and polyvinylidene difluoride (PVDF) are wildly used to assess the heart rate in health care and fitness. Especially ECG has a significant result to detect the heart function due to complete waveform (P wave and Q, R, S peaks) [27], such as heart rate variability (HRV) diagnosis. However, owing to the complex waveform of ECG, the design algorithm is complicated than PPG and PVDF. PPG sensor is extensively used in wearable devices, because the PPG sensor has simple operating characteristic (as long as it is attached to skin) and low cost. Many major companies have used this technique in smart watches or bracelets for health monitoring. However, it is very sensitive to motion artifacts (MA) and vulnerable to the impact of environmental light. In addition, the power consumption is higher than ECG and PVDF. PVDF has merits of both harvest biomechanical energy and to detect signal cycle events [30]. The PVDF sensor is bonded directly to the waveguide surface, conforms to curved surfaces, and has low mass, low profile and low cost [29]. Added to this, PVDF can be implemented to sense the sound wave, such as the microphone. This merit can be applied to blood pressure detection [32]. In terms of reducing power consumption [31] and simple algorithm, we adopt PVDF as a sensing module.

2.1. **ECG sensor.** At present, most of the studies of heartbeat detection use ECG (electrocardiogram) as sensor. The operating principle of ECG is to use an acquisition device to record the change in cardiac muscle depolarization during each heartbeat, which is described as ECG. The traditional ECG signal acquisition unit needs multiple wires and electrodes connected to human body, and sometimes needs conductive adhesive or wet electrode to help contact. It is not applicable and not an appropriate sustained home care wearable device. In recent years, the wearable devices for wireless ECG signal acquisition have been proposed for this problem [7-9,27,28]. Most of the wireless acquisition units are attached to the chest wall, it usually takes a long time to learn how to use them and they shall cling to the body to obtain good signals. Added to this, [10] proposed a novel wireless system, using a dry electrode on the plastic steering wheel, so that the ECG signal was obtained only by putting hand on it for monitoring. The ECG acquisition unit has been improved a lot, but there is still room for improvement in long-term wearing and monitoring. The ECG signal is susceptible to 50Hz and 60Hz noise from the power supply. The technology of sensing signal amplification circuit is more complex because it is influenced by skin impedance. In addition, the condition of skin contact results in the drift of input signals level.

2.2. **PPG sensor.** As the ECG cannot provide enough comfort for the users, the PPG (photoplethysmography) becomes the mainstream choice in recent years for simple operating characteristic (as long as it is attached to skin) and low cost. Many major companies use this technique in smart watches or bracelets for health monitoring [11]. Although the PPG has so fascinating characteristics, it is very sensitive to motion artifacts (MA), and the wearer's slight movement may cause this phenomenon. Therefore, how to remove MA from the PPG signal is the biggest challenge. At present, there are several common methods for removing MA, such as wavelet-based method [12], Kalman filtering [13] and empirical mode decomposition [14]. Added to this, an adaptive filtering method is designed with the assistance of accelerometer [15,16]. Other PPG sensors refer to [17,18]. The wear comfort of PPG acquisition unit is much better than ECG, and the accuracy of signal measurement is reliable. However, attaching the PPG acquisition unit to skin for a long time will cause wear discomfort. This device is not recommended for the users with skin diseases or the users who are liable to sweat. Overcome the power consumption is another main issue in designing the PPG-based wearable device. In addition, the power consumption of PPG is higher than ECG and PVDF.

2.3. **PVDF sensor.** The PVDF is a new polymeric material [19,20], a highly sensitive sensor, applicable to heart rate monitoring. Many references have studied it in [2-4]. The PVDF is characterized by flexible and thin materials that are economic especially in physiological and wearable applications where the sensor is integrated into clothing or into daily life objects. The sensor attachments to human can be minimized and the wearable device can be designed to be unobtrusive and comfortable for the user [2]. [3] presented the method through the bending-sensitive or bending-insensitive mode of PVDF materials to optimize the heartbeat signal and respiration. This is a good concept that makes good use of the PVDF characteristic and proves its usage. [4] introduces a novel wearable cardiorespiratory signal sensor device for monitoring sleep condition at home. This device consists of a belt-type sensor head which is composed with a couple of conductive fabric sheets and a PVDF film. In particular, the conductive fabric is integrated into a PVDF film, so that the device can obtain clear cardiorespiratory signals. Though the experiment in [4] demonstrated the good results by the proposed simple data processing algorithms, it is based on the designed hardware. However, this paper uses CM-01B [5], which is extensively used in the design of electronic stethoscope. It is a good electronic part for monitoring heart rate, pulse and respiratory rate. This paper focuses on developing the simple software algorithm that can easily port to embedded systems. The PVDF sensor is also used in the fetal heart sounds monitoring system for its high sensitivity and better SNR values [21]. For heart rate monitoring, the reference recommended frequency is 0.67$\sim$5HZ [22]; in other words, the heart rate is 40$\sim$300 beats per minute. The common heart rate computing mode is to filter dominant frequencies off the power spectrum. The power spectral density (PSD) function [23] can describe the composition of frequency in data, and then the heart rate is obtained by analysis [24]. However, the defect in this mode is that only the average heart rate in a period is known, not the heart rate at specific timing. Therefore, an empirical algorithm is designed by using peak or pulse edge detection for heart rate detection at present. This method will be influenced by the heartbeat amplitude or intensity. Added to this, as everybody has a different heart rate or cycle, this impact factor shall be considered in the algorithm design.

3. **Proposed Algorithm.** This paper presents our algorithm that the PVDF signal is used to estimate the heart rate. This method comprises four parts. Part 1 smoothes signals to avoid noise interference. Part 2 uses the designed PVDF sensor device to collect the wrist and heart signals, and uses DTW algorithm to judge the signal type. Part 3 selects the corresponding parameter model for peak detection according to the information of previous stage. Part 4 checks whether the peak is effective, and an evaluated heart rate value is exported at last. The process of this method is shown in Table 1.

Table 1. Steps of the proposed method

Steps	Description
1.	Smooth signal with Butterworth Low-Pass Filter
2.	Recognize the type of signals using DTW
3.	Peak detection using our empirical algorithm
4.	Calculate the heart rate with peaks found by algorithm

3.1. **PVDF sensor and hardware design.** STM32F401RE development board is based on ARM Cortex-M4 32-bit RISC core, and its frequency is as high as 84MHz [25]. The STM32F401 is connected to PVDF sensor CM-01B module, and the signal is captured and stored in the external SD card (secure digital memory card). The algorithm proposed in this paper is quite simple, it can be tested in the development board directly, and the signal can be extracted from SD card to be tested in a more efficient equipment. The device system design is shown in Figure 1.

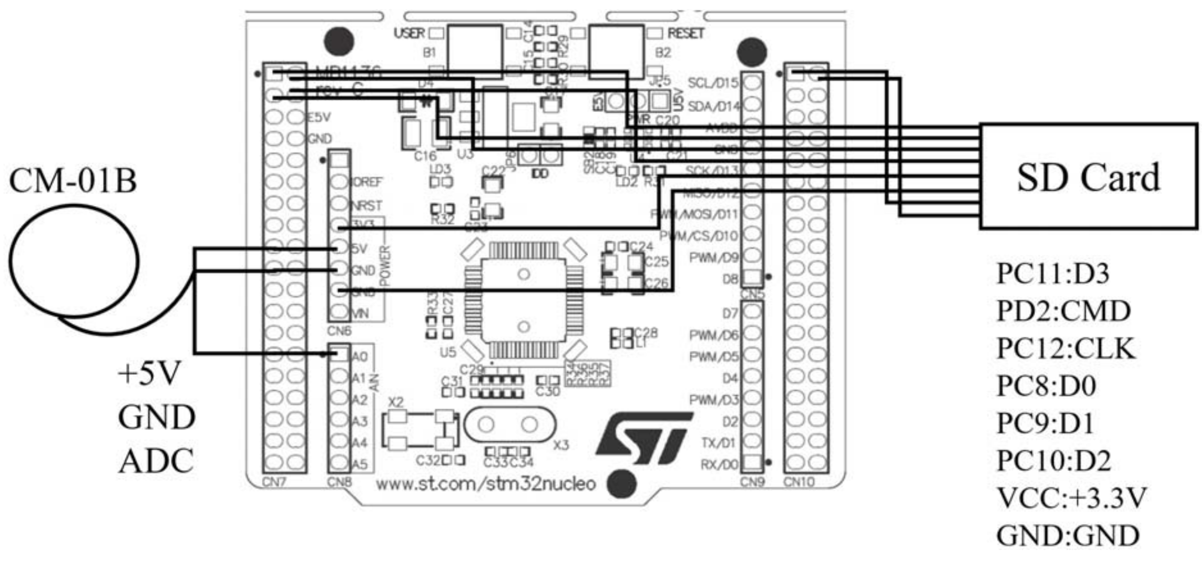


Figure 1. Overview of designed hardware system

3.2. **Preprocessing.** Even if the PVDF sensor performs well in signal acquisition, it cannot avoid the external factors distorting signals. The signal higher than the cut-off frequency is filtered by low-pass filter before signal analysis in this paper, and only the signal lower than the crossover frequency can pass through the filter to the output end. The high frequency signal is attenuated to enhance signal. This paper uses Butterworth Low-Pass Filter [26] to preprocess signals. The effect is shown in Figures 2 and 3. Figure 2(a) and Figure 2(c) show the original signal waveforms captured by the sensor on the chest. Figure 2(b) and Figure 2(d) show the results of Figure 2(a) and Figure 2(c) through the filter. Figure 3(a) and Figure 3(c) show the original signal waveforms captured by the sensor on the wrist. Figure 3(b) and Figure 3(d) are the results of Figure 3(a) and Figure 3(c) through the filter.

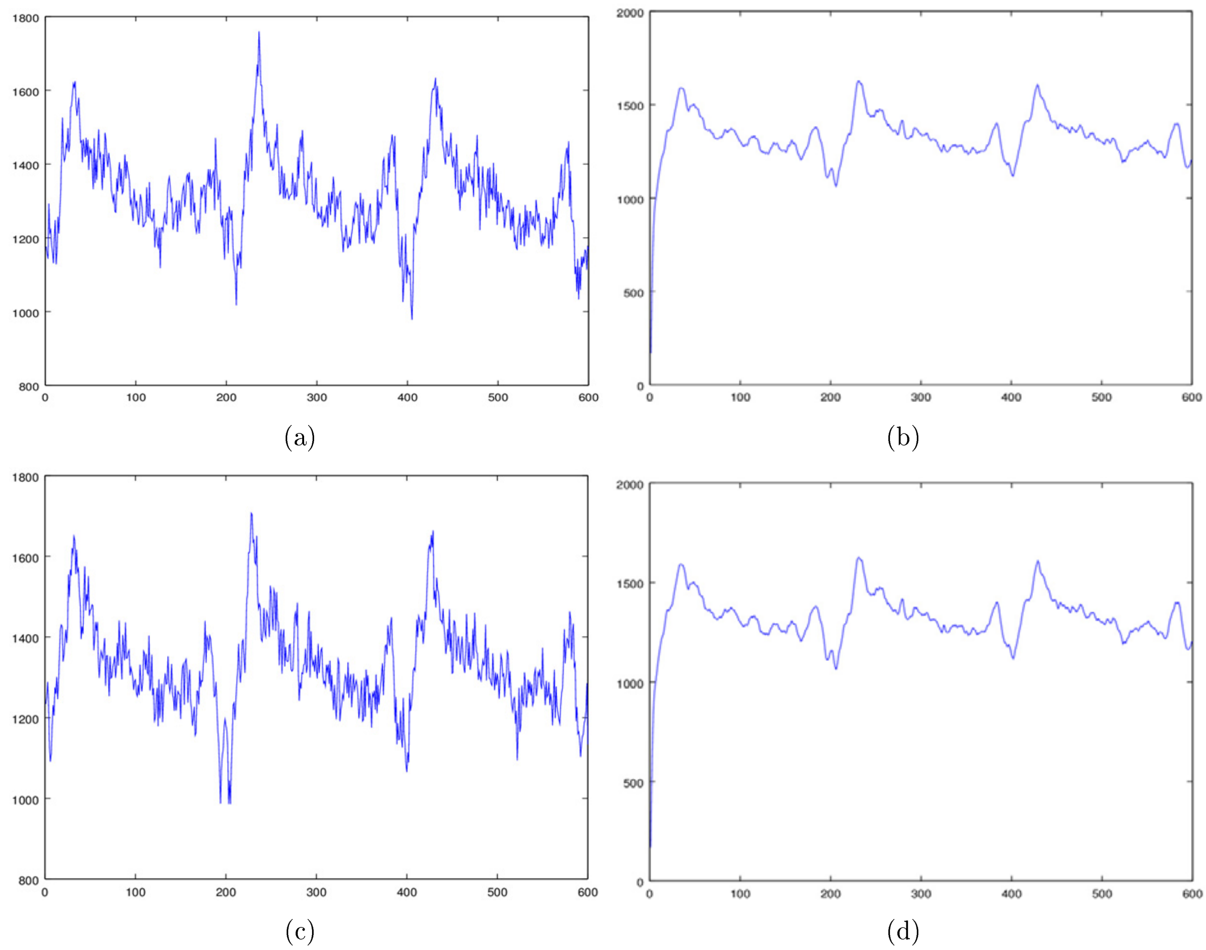


FIGURE 2. Preprocessed signals on chest wall

3.3. **DTW.** Dynamic time warping is one of the algorithms often used in speech recognition or gesture recognition. This algorithm mainly uses dynamic programming to solve the problem of different time series in signals. For example, in gesture recognition, even if one performs an action in the same way as possible every time, there are differences in the speed of the action, and the length of time series changes accordingly. However, the action tracks are similar. The DTW algorithm can correct the time series again to find out the suited track of two actions.

As each analyte has a different heart rate or cycle, this paper uses DTW to recognize wrist signal, chest signal or non-heart rate signal automatically, which contributes to

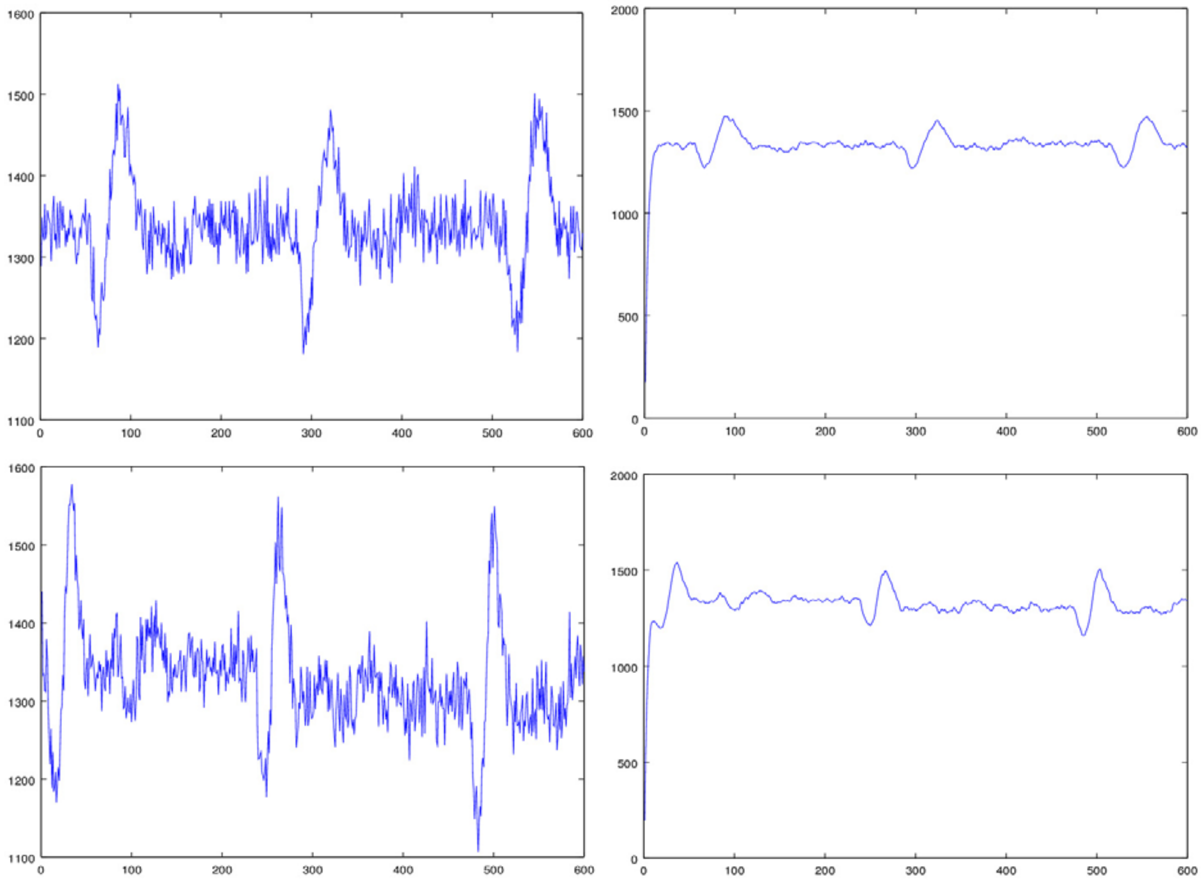


FIGURE 3. Preprocessed signals on wrist

increasing the accuracy of heart rate calculation. A lot of wrist signals and chest signals are collected as training sample set before the DTW algorithm is executed.

If R represents reference sample, there are M sample points, and if T represents test sample, there are N sample points. The mesh of T as vertical axis and R as horizontal axis is shown in Figure 4. The distance between R and T can be expressed by Manhattan distance as $d[T(n), R(m)]$, see (1); thus, the overall accumulated distance cost D can be expressed as (2).

$$d[T(n), R(m)] = \sum_{k=1}^{K} |t_{nk} - r_{mk}| \tag{1}$$

$$D[T(N), R(M)] = \sum_{n=m=1}^{N} d[T(n), R(m)] \tag{2}$$

However, in actual situation the imported track sequence length may be different each time, and the test sample and reference sample time axis variation is very large. Therefore, the local minimum accumulated cost must be considered. According to the principle of dynamic programming, the minimum path shall be extracted when deciding the local minimum path, so that the accumulated distance cost of all the cross-points on the optimal path is minimized, as shown in Figure 5. Therefore, the accumulated distance cost D can be expressed as (3). The heart rate type can be recognized automatically according to the calculated cost.

$$D[T(n), R(m)] = \min\{D[n-1, m-1], D[n-1, m], D[n-1, m], D[n, m-1]\} + d[n, m] \tag{3}$$

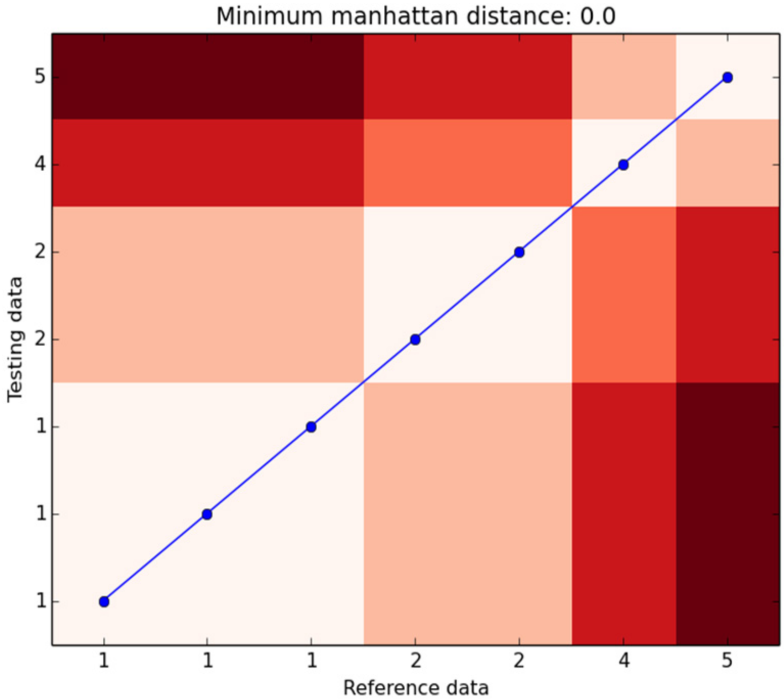


FIGURE 4. Distance and path of DTW

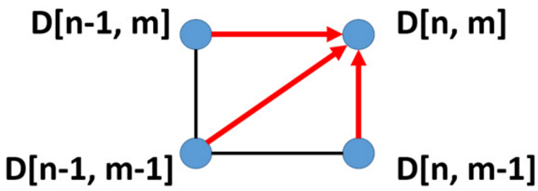


FIGURE 5. Local path constraint of DTW

3.4. **Empirical algorithm.** The signal value is obtained from the sensor, and the received signal value represents the signal amplitude. The larger the signal amplitude is, the higher the heartbeat intensity is. Let S be the signal sample set, its number depends on the sampling time t and the processing time length l. The number of set S equals l/t. For example, if the sampling time is 50ms, each signal processing time is 2 seconds, and the number is 40.

Before the heartbeat value is calculated, the minimum value and maximum value of signals are found out, and the minimum value is subtracted from each element of the signal sample set. This step is similar to removing DC (direct current) or DC bias (subtracting average value of signals from signal), so as to avoid DC bias of signal leading to errors, expressed as (4). The $\min_{dc}$ is the minimum value of set S, $\max_{dc}$ is the maximum value of set S, and offset_{dc} is the gap between maximum value and minimum value in set S.

$$\begin{aligned} &\min_{dc} = \arg\min_{x}\{x|x \in S\} \\ &\max_{dc} = \arg\max_{x}\{x|x \in S\} \\ &\forall x_i \in S, \quad x_i = x_i - \min_{dc} \\ &\mathit{offset}_{dc} = \max_{dc} - \min_{dc} \end{aligned} \tag{4}$$

The signal is quantized again by using offset_{dc} value and $scale_{value}$, expressed as (5). The $scale_{value}$ is an adjustable parameter, and it can be adjusted according to the signals captured by different sensors.

$$\forall x_i \in S, \quad x_i = 1 + \left(\frac{x_i}{\mathit{offset}_{dc}}\right) * scale_{value} \tag{5}$$

Afterwards, a simple signal filter is used to enhance the robustness of data. Moving average filter reduces the noises in the discrete time signal and increases the readability of peak by averaging the signals in the filter range. It is characterized by simple theory and rapid calculation. It is quite applicable to heart rate calculation. The BPM (beats per minute) represents the heart rate per minute numerically, and it is known that if the heartbeat is recorded once every a couple of seconds, it fluctuates in one minute, not keeping at a value. The heart rate per minute is the average value of heartbeats in one minute. However, when it is displayed as the average value per minute, if there is no drastic change in motion, the heart rate per minute is kept at a fixed value. In terms of digital signal processing theory, the part without drastic change is the low frequency part, and the quickly changed part is the high frequency part. Therefore, in terms of digital signal processing, the moving average filter is a low pass filter, the low frequency can pass the filter, and the high frequency part is filtered. The signal filtering is expressed as (6). Let MAN be the number of moving average number and $\max_{maf}$ be the maximum value in the signal set S which is updated.

$$\begin{aligned} &\forall x_i \in S, \quad x_i = \tfrac{1}{MAN} \sum_{j=-\left(\frac{MAN-1}{2}\right)}^{\frac{MAN-1}{2}} x_{i+j} \\ &\max_{maf} = \arg\max_{x}\{x \mid x \in S\} \end{aligned} \tag{6}$$

The last step is to calculate heart rate. A simple peak detection mode is used, which depends on the previous signal processing. First, a peak threshold is defined, and a peak threshold factor is designed, multiplied by maximum value of signals $\max_{maf}$ as peak threshold. It is expressed as (7).

$$peak_{threshold} = \max_{maf} * peak_{factor} \tag{7}$$

The peak value selected by this method satisfies the following conditions: (1) the peak is greater than the right adjacent signal; (2) the peak is greater than the left adjacent signal; (3) the peak is greater than the peak threshold; (4) if the peak is not the first found, it is $peak_{\mathit{offset}}$ away from previous peak. The $peak_{\mathit{offset}}$ is an adjustable parameter, as the heartbeat is regular, there will not be two peaks in a short period of time. It is expressed as (8).

$$\begin{aligned} &i_{last} \in I, \\ &peak_j = \{x_j \in S, x_j \ge x_{j-1}, x_j \ge x_{j+1}, x_j \ge peak_{threshold}, (j - i_{last}) \ge peak_{\mathit{offset}}\} \\ &I = I \cup \{j\} \end{aligned} \tag{8}$$

All the found peak index values are stored in set I. All the index values in set I are subtracted pairwise and multiplied by sampling time to obtain the pulse rate. All the pulse rates are added up and averaged to obtain an average pulse rate. It is expressed as (9). The calculation of BPM equals 1 minute divided by average pulse rate, expressed as (10).

$$\forall i \in I, \quad avg_{pluse\_rate} = \frac{1}{num(I)} \sum_{k=1}^{num(I)-1} i_{k+1} - i_k \tag{9}$$

$$BPM = \frac{60000}{avg_{pluse\_rate}} \tag{10}$$

TABLE 2. Steps of empirical algorithm

Steps	Description
1.	Calculate the minimum, maximum and the distance between min and max.
2.	Update the value of signal by reducing the minimum of signals.
3.	Scale the data by scaling value.
4.	Do moving average filter process.
5.	Calculate the peak threshold.
6.	Peak detection.
7.	Calculate the heart rate.

The empirical algorithm processing procedure is summarized as Table 2.

4. **Experimental Result.** This section evaluates the performance of the proposed algorithm.

4.1. **Experimental environment and parameter settings.** All experiments were performed on a computer with a core(TM)i5-5200U 2.20GHz Intel CPU with 4GB RAM running on Ubuntu 14.04. The basic parameter settings of all experiments are listed in Table 3. The signal is sampled 300 times per second to do analog-to-digital conversion. The signal values are normalized by scaling value. The moving average number is the window size of the moving average filter to filter out short-term fluctuations and indicate longer-term trends or cycles. In order to detect the peak correctly, the peak factor is used to adjust the threshold of peak. Finally, the peak offset is used to remove the unexpected signal that is very close to previous peak.

TABLE 3. Parameter settings for the proposed algorithm

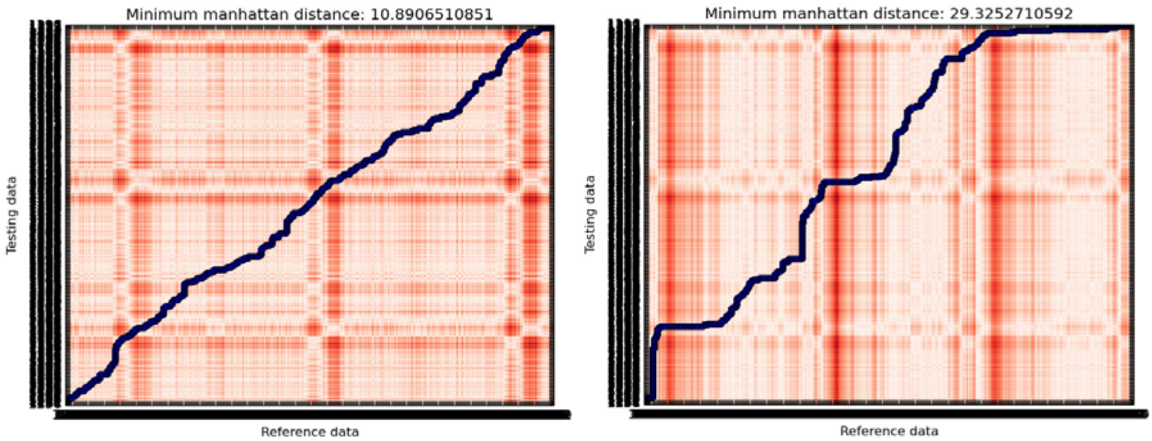
Dataset	Parameter	Value
Chest	Sampling rate	3.33ms
	Scaling value	1024
	Moving average number	10
	Peak factor	83
	Peak offset	75
Wrist	Sampling rate	3.33ms
	Scaling value	1024
	Moving average number	10
	Peak factor	90
	Peak offset	75

4.2. **Data description.** The data for this experiment are captured by PVDF sensor CM-01B module, and stored in SD card (secure digital memory card). The data are extracted from SD card, imported into computer for algorithm development and experiment. The wrist and chest signal data are collected for experiment, as shown in Figure 6. Figure 6(a) shows the device on wrist, and Figure 6(b) shows the device on chest wall.

4.3. **Using DTW to recognize signal type.** A lot of wrist and chest signals are collected by sensor. These signals are classified as training set. In order to reduce the overall experimental complexity, a training sample length is fixed at sampling time t divided by processing time length l, the same as the test sample length. In terms of the wrist and chest signals training models, the wrist signal model and chest model are

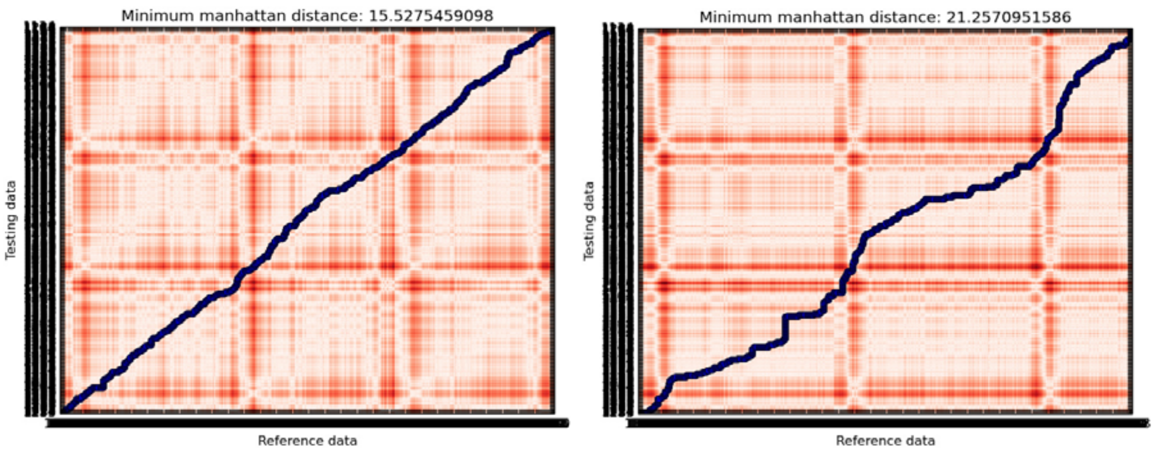
(a) (b)

Figure 6. Scenario of capturing signals



(a) (b)

Figure 7. Cost path of wrist signal



(a) (b)

Figure 8. Cost path of chest signal

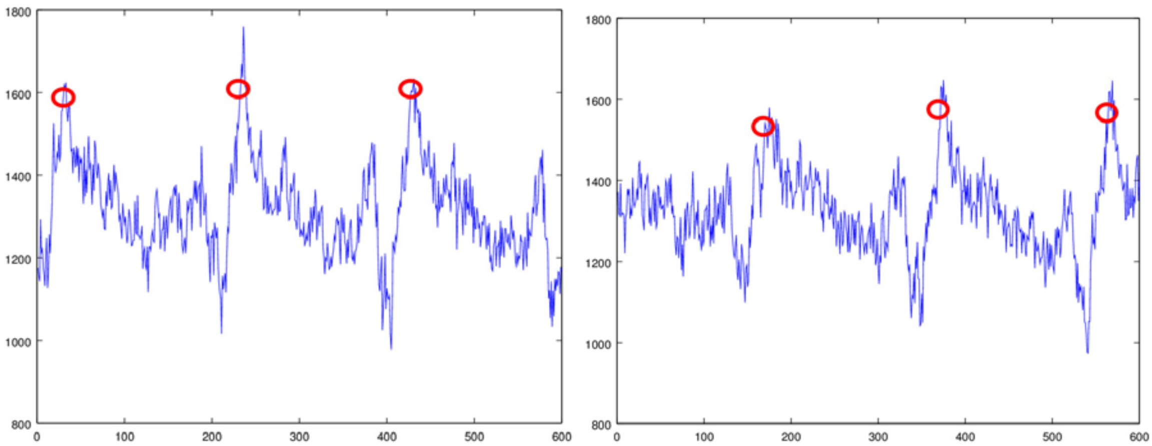
obtained by averaging. To be specific, a lot of signals are observed, which are added up and averaged to obtain a signal pattern of average value. The accumulated distance cost is obtained by actual experiment, as shown in Figures 7 and 8. Figure 7(a) shows the distance costs of wrist test signal and wrist reference signal. Figure 7(b) shows the distance costs of wrist test signal and chest reference signal. Figure 8(a) shows the distance costs of chest test signal and chest reference signal. Figure 8(b) shows the distance costs of chest test signal and wrist reference signal.

The overall test signal and reference signal data test results are shown in Table 4. The wrist-to-wrist signal maximum distance cost is 17.86. the wrist-to-chest signal minimum distance cost is 21.78. The chest-to-wrist minimum distance cost is 21.49. The chest-to-chest maximum distance cost is 17.89. According to the experimental data, the wrist and chest signals can be recognized easily by using the distance costs calculated by DTW.

4.4. **Calculating heart rate.** When the signal type is recognized by DTW algorithm, the peak detection and BPM calculation are implemented by using the corresponding parameters. Figure 9(a) and Figure 9(b) show the peaks point found corresponding to the original chest signal by the empirical algorithm proposed in this paper.

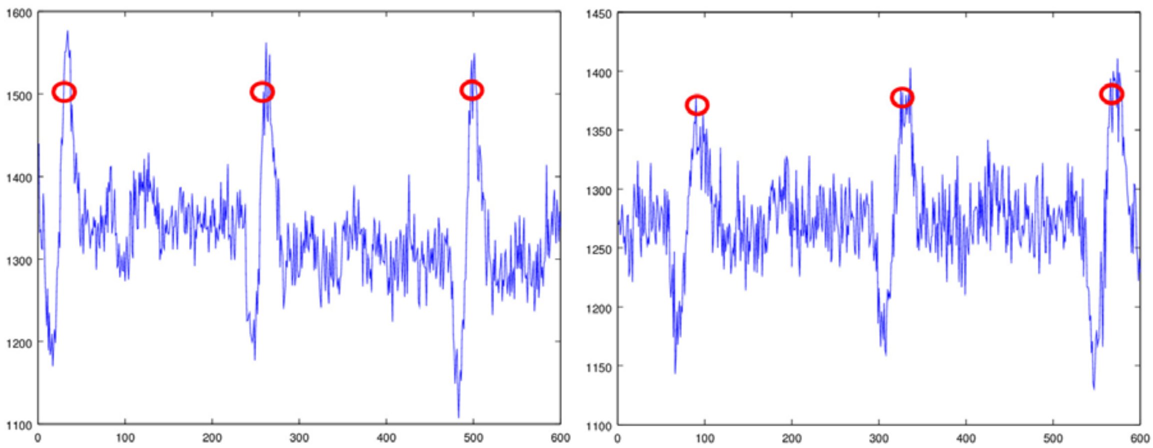
TABLE 4. The overall cost of test signal and reference signal

Testing data	Reference data of wrist	Reference data of chest
Wrist	17.86	21.78
Chest	21.49	17.89



(a) (b)

FIGURE 9. Peaks on chest signal using the proposed algorithm



(a) (b)

FIGURE 10. Peaks on wrist signal using the proposed algorithm

Figure 11. Comparison of the proposed algorithm with medical instrument

Table 5. Chest and wrist heart rate calculation comparison

Record number	Proposed algorithm	Medical instrument oximeter	Percentage error (%)
Chest 1	93.36	93.00	0.39
Chest 2	91.83	92.00	−0.18
Chest 3	93.72	96.00	−2.4
Chest 4	92.06	92.00	0.07
Chest 5	93.24	93.00	0.26
Chest 6	94.94	96.00	−1.1
Chest 7	95.96	94.00	1.8
Chest 8	89.35	89.00	0.39
Wrist 1	77.87	77.00	1.13
Wrist 2	78.21	79.00	−1.0
Wrist 3	75.92	76.00	0.11
Wrist 4	86.58	86.00	0.68
Wrist 5	78.71	77.00	2.22

Figure 10(a) and Figure 10(b) show the peaks point found corresponding to the original wrist signal. The peak point is close to the peak of signals. In order to approach the real peak, the parameter can be adjusted for optimization. However, the parameter is set so for more extensive application to everybody.

This experiment uses medical instrument oximeter for experimental comparison, as shown in Figure 11.

Table 5 shows the heart rates of chest and wrist signals. The average heart rate calculated by the proposed algorithm is very close to the reference heart rate, and the measurement error is 1 to 2%. Added to this, Figure 11 shows this experiment is developing the implementation of heart rate algorithm in the embedded system, and the heart rate is transferred to tablet PC or smart devices by Bluetooth communication. It will be a complete heart rate monitoring system in the future.

5. **Conclusions.** In order to calculate the heart rate effectively and to overcome the differences in signal amplitude and cycle, we propose an intelligent empirical algorithm integrated with DTW (dynamic time warping). According to the experimental results, the method proposed in this paper is reliable. The algorithm is quite simple mathematical operation, and it can be easily implemented in wearable systems which can be worn on the chest or wrist. It is a flexible algorithm. In the future application to life, some problems shall be overcome. For example, when the device is worn on the body, the user's talking or movement will produce additional noise. For this scenario, an effective algorithm for removing noise will be developed in the future. Added to this, the wrist and chest signal models can be trained by robuster algorithms, such as SVM (support vector machine). Thus, it can be applied to fitness or care to enhance human welfare.

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