Article

Signal Quality Valuation with Optimal Power Consumption and High Compression Ratio Method for Estimate Heart Rate Applied to Real-time PPG Measurement

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Abstract: Nowadays, wearable devices for human health monitoring are increasingly become popular and widely used. Typically, the wearable device is small size and operates with batteries. Therefore, the wearable device acquires bio-signals and transfers to smartphones or personal computers (PC) via WiFi/ Bluetooth for processing data. To reduce power consumption is one of the most important challenges of designing wearable devices. To solve this problem, the proposed signal quality valuation (SQV) method can be select the high-quality signal and reduce the transfer time to other devices. In this paper, the proposed SQV and data compression method rely on real-time PPG signals analysis to retain important information of PPG signal, improve performance and power consumption of PPG devices. Besides, we also proposed Heuristic rules for heart rate (HR) estimation with compression data. The experimental results show that the highest compression ratio (CR) is 387.8 with BIDMC Physionet database (sampling frequencies of 125 Hz) and HR error as 1.43 bpm for averaging absolute error (avAE), the standard deviation absolute error (sdAE as 0.4) and relative error mean (avRE as 0.019). The proposed real-time PPG measurement system (sampling frequency as 100/ 200/ 400 Hz) reduce power consumption and open the new structure for healthcare application systems.

Keywords: Lossy/ lossless compression; Huffman coding; real-time PPG measurement; heart rate estimate; Message Queueing Telemetry Transport (MQTT), healthcare system

1. Introduction

The applications of PPG signal have increasingly become the most popular include: saturation of peripheral oxygen (SPO$_2$), blood pressure (BP), heart rate (HR) [1-4]. The typical PPG sensor has three different LEDs (red, blue, green) with wavelength among 660 nm to 940 nm (generated by alternating stimulation of two photodiodes) to measure oxyhemoglobin (HbO$_2$) and deoxyhemoglobin (Hb) in arterial blood and estimate BP, SpO$_2$ [2]. There are many methods of estimating blood pressure based on PPG signals such as: pulse transit time (PTT) method using both PPG and ECG signals at the same time to estimate BP[5, 6]. Multi-regional of PPG signal have also been used to evaluate vascular diseases such as occlusion, vascular aging, and tissue perfusion. Therefore, the analysis of the components of the PPG signal is essential in many applications [4, 6, 7].

The message queuing telemetry transport (MQTT) protocols is a simple and popular technology for developing of Internet of Things (IoT) system[8-10]. There are a lot of application related MQTT such as manufacturing, public administration, environment, building automation, and healthcare[1, 11, 12]. The MQTT system provides an indirect channel (via a broker) between the publishers (where data produce) and subscribers (where data consume). The main purpose of broker classifies data of topics and sends them to the subscribers who need data follow the topic for processing[8, 9]. To optimize the resource-constrained of PPG device with limited processing ability, the proposed MQTT with simple structures applied to smart healthcare system[13]. However, the MQTT broker

based on personal computer (PC) can provide the high performance computing to deploy the compression algorithm for optimization data processing and transferring [14-16].

In recent decades, the bio-sensors have great developed with reducing the size, integrated processing and radio-frequency (RF) modules which have allowed to design wireless wearable device for collecting the vital signal from human body [16, 17]. The compression of bio-signals can provide two benefits of wearable devices: 1) reduce the memory for storing data (or buffering); 2) reduce the transmission time and power consumption of device [15, 18]. In general, there are two compression methods [25] which are the direct compression and indirect compression method [19-21]. The indirect signal compression could analyze signals based on the transform method such as Fourier, wavelet, etc. ... to remove unnecessary components in the signal [18, 22-25]. This method will retain the characteristics of the signal depending on method used to analyze the signal. The direct compression method will be analyzed in time domain and retain only the specific components of the signal. Hence, the direct method applies only to certain types of signals with special cases[26, 27]. The typical PPG signal has a relatively simple shape which the signal components are well defined and suitable for direct compression. Besides, the Huffman encoding is a popular technique commonly used to reduce data frames on the transmission line based on assigning values to highly repetitive data [15, 23, 26]. To reduce the size of PPG data, the proposed applied two compression techniques to PPG signal obtain a relatively high compression ratio better than other compression methods.

For the elderly, blood pressure (BP) and HR are usually higher than young people and usually around 60-150 beats per minute (bpm) and monitor HR is important [28]. Normally, the original PPG data includes a lot of noise, the HR calculation algorithm is relatively complex and low accuracy [3]. The proposed data compression algorithm reduces the length and complexity of PPG data to focus on peak values more consistent with HR calculation algorithms. We recommend heuristic rule suitable with compress data to apply HR calculation.

The layout of this paper is as follows. The related works section provides a brief description of the studies from other authors involved data compression. In the method section, we focus on analyzing the smart healthcare monitoring system, optimize power consumption of PPG device and direct compression data for PPG. Testing and results, the performance with a real prototyping PPG device to measure current consumption during operation and compression-decompression using PPG data in several Physionet, real-word databases[29, 30], and volunteers' signals. The effect of compression on the PPG diagnostic metric and other factors such as the signal's sampling frequency and wave morphology. Finally, section 5, summarizes the main advantages and disadvantages of the proposed method.

2. Related works

In this section, we presented the previous works of other authors related to bio-signal compression. Mustafa Emad Hameed et al., presented the compression method of the ECG signal to use the buffer block, peak detection, compression data, and encoding mechanism to allow seamless and safe transmission of the ECG signal from the sensor to display device [23]. The encryption method using the Huffman encryption discrete wavelet transform and Cipher Block Chaining-Advanced Encryption Standard algorithm.

Simhadri Vadrevu et al. proposed a method of real-time data compression to maximize battery life for wearable devices. Their research was conducted on an Arduino Due with the 32-bit Atmel SAM3X8E ARM Cortex-M3 processor. The CR achieves from 7 to 28 with energy savings between 83% and 92% [31].

Deboleena Sadhukhan et al. presented a data compression technique PPG based on practical band estimation from signal characteristics. Each data block represented using the corresponding discrete Fourier transform coefficients. The algorithm achieves an overall CR of 35.95 with signal distortion maintained below 4% [22].

Ozal Yildirim et al. presented a study that proposed a new deep convolutional encoding (CAE) model for compressing ECG signal. The paper describes a 27-layer deep neural network structure for comprising encryption and decryption components.

S. Dhar et al. presented a study that proposes PPG digitizing samples to be passed through a low-pass filter (IIR Butterworth method) to eliminate high-frequency noise. The ASCII techniques used to reduce the size of data. This method achieves an attractive

compression (CR = 122.24, percent root mean square difference (PRD) = 0.02%, Cross-Correlation coefficient = 0.998845, etc.) [32].

Rajarshi Gupta presented a lossless, real-time compression technique based on the combination of quadratic delta and Huffman encoding for PPG signals. The author performed a compression algorithm with 10 bit PPG data at the sampling frequency of 125 Hz to achieve the CR of 2.223, PRD, and percent root mean square difference normalized (PRDN) reached 0.127 and 0.187 [20].

K.R. Arunkumar et al. have studied HR estimation based on PPG signals from wrist-type. The PPG signal includes noise from motion artifacts. Hence, the proposed method consists of using FFT analysis and 3-axis accelerometer sensor to remove the noise from the PPG signal. Although, the method is relatively accurate with an error of 1.86 bpm, which is complicated to apply for wearable devices with low computational ability [3].

From the studies of the above typical authors, we found that no studies have performed direct compression of PPG signals. Therefore, we proposed and perform this study with the time domain analysis of PPG signal. These analyzes remove unimportant components to achieve a high compression ratio without sacrificing the characteristics of the PPG signal. The proposed smart healthcare system with wireless PPG device can be increase the battery life and open the new applications of clinical diagnostic

3.   Materials and methods

A typical architecture of real-time PPG measurement system is shown in Fig. 1. There are three parts, including a PPG device, a MQTT broker and a display device such as smartphone or PC. The PPG device acquires the bio-signal from human body. The main requirements of PPG device are small size, low power consumption and high quality data collection. The MQTT broker is a bridge connect among PPG devices and display devices, which receive the data from the PPG device. The display device provides the user application for analyzing, processing data and display results. In this section, we proposed SQV method for optimizing the power consumption of PPG device based on detection and collection helpful PPG signal and data compression method based on the main characteristics of PPG signals.

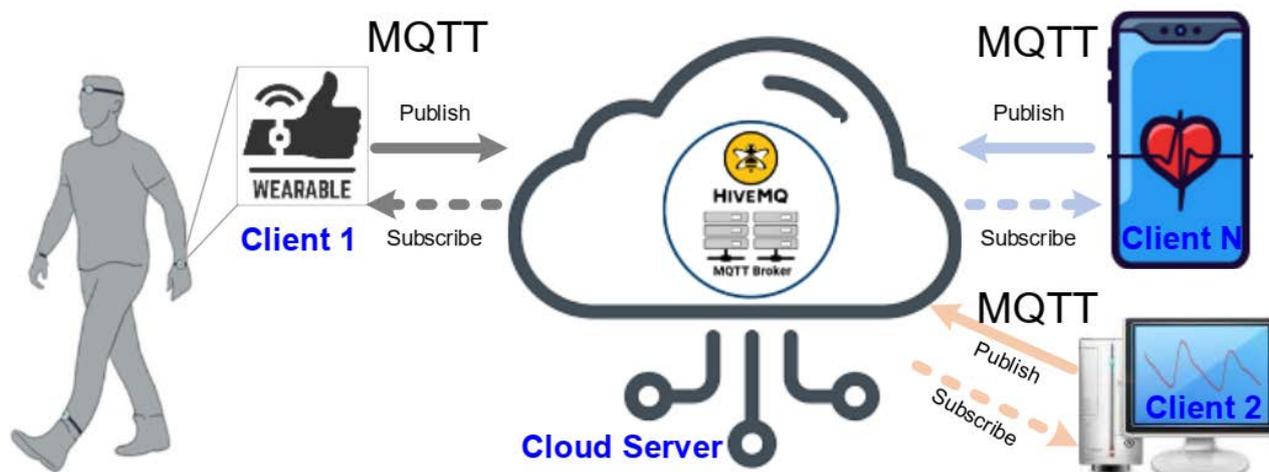**Figure 1** Typical smart healthcare system with PPG measurement.

3.1.   Control PPG sensor and analysis PPG waveform

A typical PPG waveform is provided in Fig. 2(a). The signal consists of two components: the vibrating alternating current (AC) component (reflecting changes in arterial blood volume) and direct current (DC) composition (mainly representing tissue and effect of venous blood) [7].
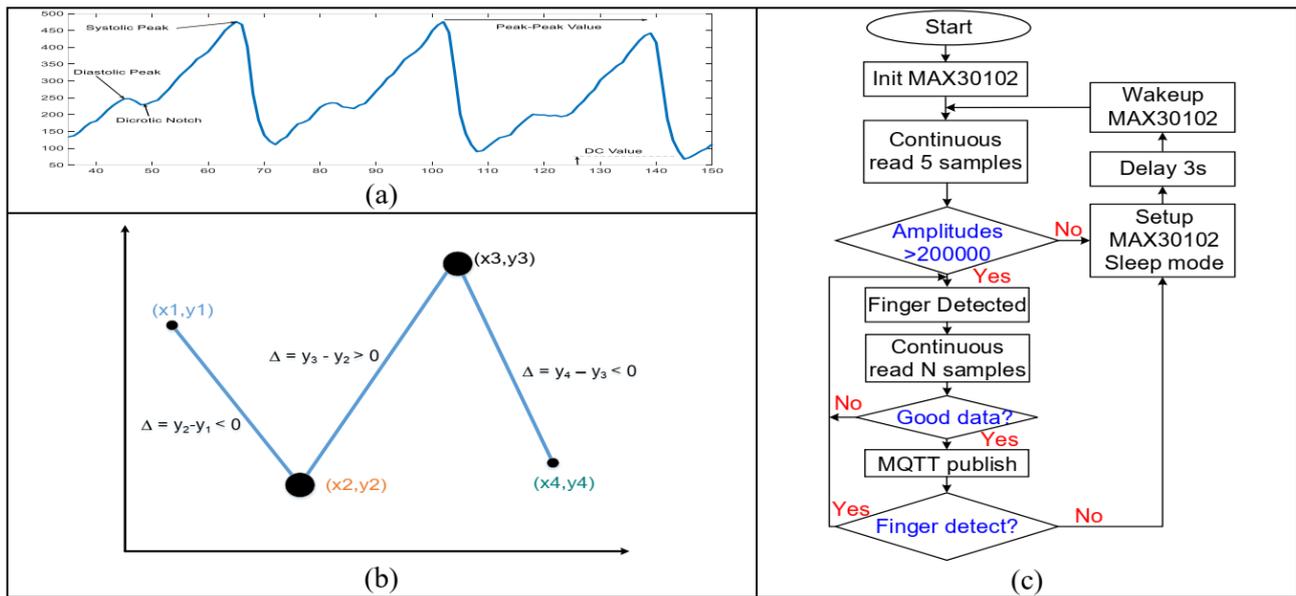
Figure 2 Typical PPG waveform: (a) typical PPG signal [43], (b) characteristic of Δ, (c) proposed firmware block diagram.

Fig. 2(a) shows a typical PPG signals which are characteristics such as the systolic peak, the diastolic peak. However, the signal has highest and lowest points which are shown clearly. Based on features, the proposed a direct compression method to retain the above characteristics.

To optimize the data processing, the system need to process the high quality PPG data and automatic remove the part of PPG data with heavy noise or without finger. We proposed SQV algorithm based on MCU to control the PPG sensor which acquire the PPG data with finger. The detail algorithm shows in Fig. 2(c).

The operation of proposed focus to detect the finger and the amplitude of signal before the system acquire the PPG data. Normally, the PPG sensor is in sleep mode with a really small current consumption, with the cycle as 3 seconds the MCU send the wakeup command to PPG sensor via I2C interface and read 3 PPG samples. To compare these PPG data and MCU make decision continuous to read PPG data or go to sleep mode.

3.2. Proposed compression method

To reduce the number of computation, we removed the DC part and only focus on the AC part of PPG signal by following formula below.

$$x(i) = x(i) - \min(x) \qquad (1)$$

Convert the AC part into new n-bit resolution data according to the formula:

$$x(i) = \frac{x(i) * 2^n}{\max(x(i))} \qquad (2)$$

To calculate the different value of two consecutive PPG values, follow the formula.

$$\Delta(i) = x(i + 1) - x(i) \qquad (3)$$

Where: $x(i)$ is PPG samples, $\min(x)$ the minimum of PPG sample.

Fig.2(b) shows the relationship between Δ value and the shape of graph. The definition a special point follows the Δ value. The simple special point follows the Δ sign which changes from positive to negative or from negative to positive. Therefore, we focus on retaining these unique positions based on the sign of Δ in formula (3).

The proposed compression algorithm based on Δ sign described in pseudocode below:


```
Algorithm 1: Compression Algorithm
   Input: Origiginal PPG Signalt
   Output: Compression Data
 1 Function Min(PPG):
 2     min = PPG(0)
 3     for i = 1 to len(PPG)... do
 4         if (min ≤ PPG(i)) then
 5             min ← PPG(i)
 6     return min

 7
 8 Def Offset-PPG(PPG):
 9     offset = Min(PPG)
10     for i = 0 to len(PPG) − 1... do
11         PPG(i) ← PPG(i) − offset
12     return PPG

13
14 Def Cal-Delta(PPG):
15     data = Offset-PPG(PPG)
16     for i = 0 to len(data) − 1... do
17         Δ(i) ← data(i + 1) − data(i)
18     return Δ

19
20 Function Main:
21     Δ = Cal-Delta(PPG)
22     CR(0) ← PPG(0)
23     j ← 1
24     for i = 0 to len(Δ) − 1... do
25         if (Δ(i) ≤ 0 ∪ Δ(i + 1) ≥ 0) ∩ (Δ(i) ≥ 0 ∪ Δ(i + 1) ≤ 0) then
26             CR(j) = PPG(i)
27             CR(j + 1) ← i − CR(j − 1)
28             j ← j + 2
```

```
Algorithm 1 Huffman Encoding
   Input: PPG data
   Output: Output and Binary coding
 1: Create a Dic contain PPGdata follow (minimum to maximum
 2: j ← 0
 3: for i = 1 to len(PPG)... do
 4:     if PPG(i) < PPG(i + 1) then
 5:         Dic(j) ← PPG(i)
 6:         j ← j + 1
 7:     else if PPG(i) > PPG(i + 1) then
 8:         Dic(j) ← PPG(i + 1)
 9:         j ← j + 1
10:     end if
11: end for
12:
13: Let count the element of table in the array [1...n]
14: for i = 0 to len(Dic) − 1... do
15:     if Dic(i) ∈ PPG then
16:         weight(Dic(i)) ← weight(Dic(i)) + 1
17:     end if
18: end for
19:
20: Let node be an empty array
21: k ← 0
22: for i = 1 to len(Dic)... do
23:     if weight(Dic(i)) > 0 then
24:         Create node(k) contain (Dic(i), weight(Dic(i)))
25:         k ← k + 1
26:     end if
27: end for
28:
29: Arrange node with weight from low to high
30: for i = 0 to len(weight) − 1... do
31:     if weight(i) > weight(i + 1) then
32:         node(i) ⇐ node(i + 1)
33:     end if
34: end for
35:
36: Calculate and arrange node of Huffman tree
37: for i = 0 to len(Dic) − 1... do
38:     l ← weight.node(0)
39:     binary(i).node(0) ← 0
40:     r ← weight.node(1)
41:     binary(i).node(1) ← 1
42:     newnode ⇐ Dic(node(1), node(0)), weight(l + r)
43:     Re-Arrange newtree with newnode
44: end for
45:
46: The rootnode at the end of forloop
47: Let output is combine rootnode and binary
48: output ← Dic(rootnode) + binary
```

(a)   (b)

Figure 3 Proposed pseudocode of: (a) compression method, (b) Huffman encoding

3.3. Data transfer frame with Huffman encoding

Fig. 4 shows PPG data after applying the proposed compression method. The new PPG data contain the special points related delta value which is define in formula (3).

PPG(0)	PPG(i)	i	PPG(j)	j-i
…	PPG(k)	k-n	PPG(x)	x-k-n
PP(x): value of sample point need to keep				
i: number of samples point as reduce				

Figure 4 Packet of data after compression

To reduce the length of data frame before transmit to other devices, we applied the Huffman encryption algorithm which re-arranges data frame follow the reputation of PPG value. The Huffman algorithm shows in pseudocode below.

Fig 2(b) describes the Huffman encoding in 6 steps.

Step 1: Line 1 to 11. To generate a Huffman cipher from the PPG data which describe in Fig. 4. The values of Huffman algorithm arrange from smallest to largest.

Step 2: Line 13 to 18: Calculate the number of repetitions of each data.

Step 3: Line 20 to 27: Create nodes in Huffman tree with data in step 1 and 2.

Step 4: Line 29 to 34: Arrange nodes follow weight of nodes.

Step 5: Line 36 to 43: Recalculate the weight of the new Huffman tree and re-arrange the new Huffman tree follow the new weights of new nodes.

Step 6: Lines 46 to 48: create a new data frame after compression ends.

To evaluate the proposed compression method, we used the compression ratio (CR) parameter which is described below [29].

$$CR = \frac{Original\ (bit)}{Compression\ (bit)} \qquad (4)$$

3.4. Re-construct and evaluate PPG signal

Fig. 3 shows the proposed reconstruct the PPG signal. In this study, the reconstruct PPG signal contains two steps: 1) Huffman decompression, 2) linear interpolation of the missing data. The linear interpolation values are calculated by using the formula below.

$$PPG_{val(y)} = \frac{PPG(j) - PPG(i)}{i} * y \qquad (5)$$

To evaluate the PPG signal after decompression algorithm, the efficiency of the decompressor was estimated by computing the PRD and PRDN.

$$PRD = 100 * \sqrt{\frac{\sum_{k=1}^{N}(x(k) - \widehat{x(k)})^2}{\sum_{k=1}^{N}(x(k))^2}} \qquad (6)$$

$$PRDN = 100 * \sqrt{\frac{\sum_{k=1}^{N}(x(k) - \widehat{x(k)})^2}{\sum_{k=1}^{N}(x(k) - \bar{x})^2}} \qquad (7)$$

Where $x(k)$ is the original sample, $\widehat{x(k)}$ is the corresponding decoded sample, and $\bar{x}$ is the average of the original sample array.

3.5. Heuristic rule for estimating heart rate

The proposed method calculate HR based on the peak values determined in Fig. 4 which contain special points (systolic peak). We proposed the heuristic rules to estimate HR as follows:

Rule 1: The HR is between 60 and 130 beat per minute (bpm).

Rule 2: To calculate HRi in each 10 seconds (data frame as 10 s), corresponding to the 100 Hz or 125 Hz sampling frequency.

Rule 3: Determine position of 2 nearest peaks (d) within 10 s of PPG signal to calculate the number of HR (avoid confusion diastolic peak with systolic peak). Repeat 6 times to calculate the average HR for 1 minute. This is also the most important rule to calculate HR. For example, at 100 Hz sampling frequency, PPG data describes in Fig. 4. and data frame with 10 s signal collection. The values (i), (j-i), ..., (k-n), (x-k-n) satisfy the following condition.

$$70 \leq (i), (j - i), \ldots, (k - n), (x - k - n) \leq 100 \qquad (8)$$

Rule 4. The estimate HR value is not higher than 30 bpm within 10 s.

The Absolute Error (AE), Average Absolute Error (avAE), Standard Deviation of the Absolute Error (sdAE) and Average Relative Error (avRA) used to evaluate the accuracy of HR estimation:

$$AE_i = |HR_{est}(i) - HR_{true}(i)| \qquad (9)$$

where $HR_{est}(i)$ and $HR_{true}(i)$ denote the estimated and the true HR value in the i_{th} time window in BPM.

$$avAE = \frac{1}{N}\sum_{k=0}^{N} AE_k \qquad (10)$$

$$sd\text{AE} = \sqrt{\frac{1}{N}\sum_{k=0}^{N}(AE_k - av\text{AE})^2} \qquad (11)$$

$$av\text{RE} = \frac{1}{N}\sum_{k=0}^{N}\frac{AE_k}{HR_{true}(k)} \qquad (12)$$

where N is the total number of estimates (number of windows). These metrics are reported for each recording

4. Results and discussion

To evaluate the efficiency of the proposed signal compression method, we conducted the tests with the database provided by Physionet (12-bit, 125 Hz) [43] and Real-World (50 Hz) [44]. We also used module ESP8266 and module MAX30102 to collect real-time data from volunteers and perform a signal compression algorithm to these signals. We used Python software v.3.7 for analyzing and evaluating data.

4.1. Evaluate the performance of signal compression with Physionet and Real-World database

We experimented with the PPG signal compression algorithm with MIMIC II from Physionet and Real-World. The MIMIC II Physionet database contains five records such as PPG, respiratory, and ECG signals from more than 90 patients. The characteristic of PPG signal is 12-bit resolution and 125 Hz sampling frequency, including 6000 samples corresponding to the time of 8 minutes [43]. The real-world database contains PPG signals from 35 healthy people with a sampling frequency of 50 Hz that each PPG signal contains 300 samples (6 seconds recording) with a sampling rate of 50 samples/ sec [44].

We used 1250 PPG samples from MIMIC II database and 300 PPG samples from Real-World database to perform a data compression algorithm. To evaluate the compression and decompression algorithm, we used three parameters: CR, PRD, and PRDN.

Figure 5 Test results with MIMIC II data: (a) Physionet, (b) Real-World

Table 1 The comparison of main parameters of differences compression method.

Authors	Techniques used	Fs (Hz)	CR	PRD (%)	PRDN (%)	Computational complexity	Comments

Chong et al.[16]	Delta Modulation	1000	16	0.392	x	O(N)	- Computational burden- Low - Speed- High - Memory Requirement- Low - Noise sensitivity- High - Others- Operates only at high sampling rates
Simhadri Vadrevu et al.[31]	High-Pass Filtering, Discrete Cosine Transform (DCT), Threshold Estimation and Significant Coefficient Estimation	125	30.57	7.9	x	$O(N^3)$	- Computational burden- High due to the filter, DCT and estimation - Speed- Low - Memory Requirement- High due to adaptive data thresholding. - Noise sensitivity- Low
Mukhopadhyay et.al [33]	Inter-sample differencing, grouping and ASCII character encoding	125	30.27	0.22	0.33	O(N) (without considering the pre-filtering stage)	- Computational burden- High due to pre-filtering using 4th order Butterworth filter. - Speed- Moderate - Memory Requirement- Medium due to need of data grouping - Noise sensitivity- High - Others-Simple implementation
Dhar et al.[32]	Inter-sample double differencing, grouping and	500	122.4	0.02	0.33	Compression – O(N) (without considering the pre-	Computational burden- High due to pre-filtering using low-pass IIR

	ASCII character encoding					filtering stage) Decompression – $O(N^3)$ (for cubic interpolation)	butterworth filter of order 9 • Speed- Low (considering higher order • filtering) • Memory Requirement- Medium due to need of data grouping • Noise sensitivity- High • Others-Relies on initial down sampling
Deboleena Sadhukhan et al.[22]	Adaptive band limit estimation, computation and optimal encoding of Fourier Transform coefficients	125	35.95	3.88	6.21	$O(N^2)$	• Computational burden- Low (except for the first data segment where the band limit is estimated) • Speed- Medium • Memory Requirement- Low (except for the first data segment) • Noise sensitivity- Low • Others- Noise robust, reduced effect of Gibb's phenomenon, Optimized compression gain.
This worked	Delta Modulation, Segments analysis	**125**	**387.8**	34.8	56.4	**O(N)**	• Computational burden- **Lowest** • Speed- **Highest** • Memory Requirement- **Lowest**

- Noise sensitivity-High
- Others- **Simplest implementation**, the reconstruct data depend on the algorithm for predict data

'The 'O" notation described computational complexity, that is the number of operations with data length ''N".

Table 1 shows the comparison of the proposed method with previous studies, the results described in below. Details of the test results with the MIMIC II and Real-World databases are described in Table 2.

The results show the highest CR reached 387.5 (Bidmc-04) [43] higher than 3 times compare with previous study 122.4 (500 Hz) [31] while maintaining at a sampling frequency of 125 Hz. There are two main reasons why the proposed compression method achieves a high compression ratio. The first reason, we removed the DC part of the PPG signal according to formula (1). The second reason, the PPG signals have not many breakpoints, most of the data is removed by leaving only values (max and min values) in calculation cycles. However, the signal distortion is relatively high because we used the linear interpolation method to restore the signal. The highest and lowest peaks are always guaranteed, which means HR calculations with post-decompression signals are consistently accurate.

Table 2 The comparison CR, PRD, PRDN from different sources of PPG signals [34, 35].

Data Source	Samples	CR	PRD(%)	PRDN(%)
Bidmc-01	1250	14.0682	16.0661	27.5106
Bidmc-02	1250	77.6305	14.0901	27.7662
Bidmc-03	1250	129.9076	27.9731	59.1093
Bidmc-04	1250	**387.8**	**34.79811**	**56.4014**
Bidmc-05	1250	38.8928	9.4405	24.319
Real-World (A)	300	8.0961	9.5395	23.6528
Real-World (B)	300	11.2965	12.7527	25.1094
Real-World (C)	300	10.3247	9.595	20.2545
Real-World (D)	300	**12.2863**	**9.7356**	**18.4858**
Real-World (E)	300	9.818	11.8956	25.0628

Table 2 describes only CR, PRD, PRDN parameters of the signal compression method with specific tests. For Real-World databases, the highest compression ratio is still 12.2863 even though the sampling frequency is only 50 Hz. However, the parameters of PRD, PRDN are relatively high compared to other methods.

4.2. Heart rate estimate with Heuristic rule

We used the BIDMC database (01-03) to HR estimation of heuristic rules with the compression data. The results described in Tables 3 and Fig. 6.
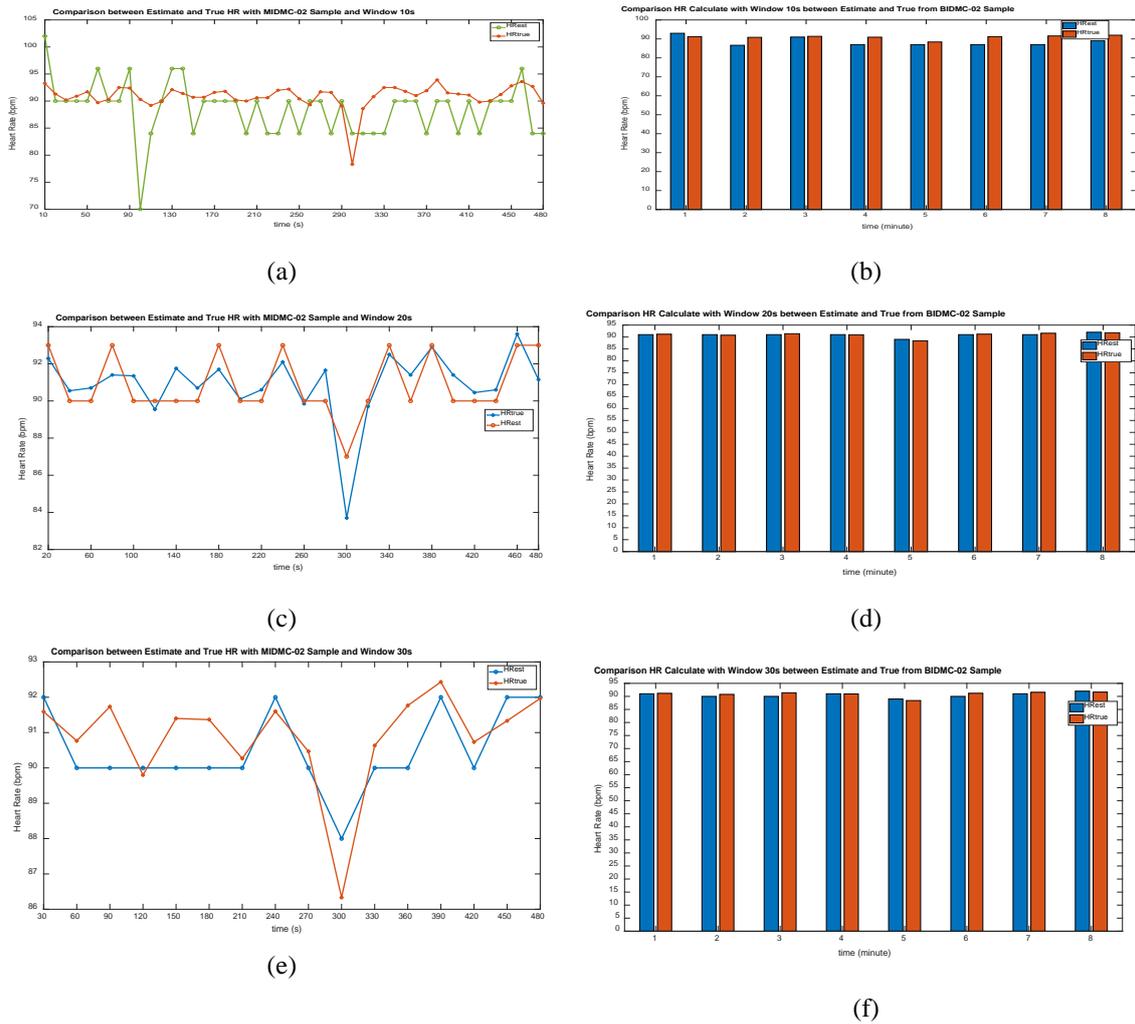
(a)

(b)

(c)

(d)

(e)

(f)

Figure 6 The comparison between estimate and true heart rate with sample bidmc-02: (a, b) window as 10s, (c, d) window as 20s, (e, f) window as 30s.

Table 3 The comparison estimate and true HR with window as 10 s, calculate avAEi, sdAE, avRE from different sources of PPG signals

Data source	Time(s)	HRtrue	HRest	avAEi	sdAE	avRE
Bidmc-01	$0 \rightarrow 60$	93.023	91	4.39	2.114	0.0473
	$61 \rightarrow 120$	**91.47**	**86.67**	**6.367**	**1.97**	**0.0692**
	$121 \rightarrow 180$	91.32	91	3.55	2.234	0.038
	$181 \rightarrow 240$	91	93	4.63	1.831	0.051
	$241 \rightarrow 300$	91	89	2.67	2.426	0.029
	$301 \rightarrow 360$	91.27	89	3.83	2.836	0.042
	$361 \rightarrow 420$	90.77	87	3.55	2.763	0.039
	$421 \rightarrow 480$	**90.67**	**92**	**2.27**	**2.24**	**0.025**
Bidmc-02	$0 \rightarrow 60$	91.21	93	3.19	3.17	0.035
	$61 \rightarrow 120$	**90.77**	**86.67**	**5.33**	**5.23**	**0.059**

	121 → 180	91.28	91	3.22	2.06	0.035
	181 → 240	90.93	87	3.93	3.05	0.043
	241 → 300	90.42	87	3.83	2.81	0.044
	301 → 360	91.2	87	4.2	2.71	0.046
	361 → 420	91.58	87	4.58	2.64	0.05
	421 → 480	91.65	89	3.45	2.91	0.038
Bidmc-03	0 → 60	76.05	76	2.55	1.01	0.034
	61 → 120	76.63	75.67	2.8	1.6	0.037
	121 → 180	77.28	75	4.08	2.91	0.052
	181 → 240	76.18	76	2.58	1.29	0.034
	241 → 300	75.65	78	2.35	0.24	0.031
	301 → 360	78.57	76	3.4	2.15	0.043
	361 → 420	**76.57**	**78**	**1.43**	**0.4**	**0.019**
	421 → 480	76.18	75	3.75	3.04	0.05

Table 3 shows the estimate HR values with data frames corresponding to 10 seconds (data frame as 10 s). The HR value (HRest) calculates from 10 seconds and the HRtrue value is the average value of HR in 60 s (sources bidmc_xx_Numerics.csv). The results show that the bidmc_01 data have maximum HR error (AEi) as 6,367 bpm (between 60 s-120 s) and minimum error (AEi) as 2.27 bpm (between 421 s-480 s). After checking the bidmc_01 signal (source bidmc_01_Signals.csv), we found that within (60 s-120 s) the signal was heavily disturbed and it is not impossible to recognize as a PPG signal. The same problem occurs with the bidmc_02/03 data. For the bidmc_03 data the minimum HR error (AEi) is only 1.43 bpm (between 361 s-420 s).

We selected bidmc_02 data for evaluating of heuristic rules with different data frames (data frames as 10 s, 20 s, 30 s). The results depicted in Fig. 6. In Fig. 6 (a, c, e) describe the estimate of HR corresponding to data frames as 10 s, 20 s, 30 s. The data frames 20 s, and 30 s the ability to estimate HR is relatively accurate with smaller internal error 2 bpm, with anomalies less than 3 bpm (270 s-330 s). Fig. 6 (b, d, f) describes the 1-minute average HR corresponding to 10 s, 20 s, and 30 s data frames. For data frame 20 s and 30 s, the estimated HR per minute is less than 1.5 bpm.

The calculation of heuristic rules is also simple and easy deployed to low performance MCU lines

4.3. Current consumption of PPG sensor analysis

Fig. 7 shows the current measurement model and current consumption waveform during the operating of PPG sensor. The operation of PPG sensor contains two modes 1) Sleep mode without finger detection, 2) Normal operation with finger. The current consumed by the proposed method is 3.2 mA for operating mode the 3 sec PPG data that includes the feature computation and decision rules for selecting the high quality PPG signal. The total current consumed by the proposed PPG device is 23 mA, which includes the current consumption of 20 mA for collecting, check the quality PPG data, and continuous transmission of PPG data using the UART module based on Arduino platform. Table 4 shows that the current consumption proposed PPG device can reduce operation current consumption from 23 mA to 145 mA for proposed finger and without finger detection mode, respectively. The proposed method improves the battery life of low power PPG devices where in optimize the current consumption of sensor with monitoring the quality of data. Transfer PPG data through WiFi consumes the current higher the 6.3 times compare with UART interface.
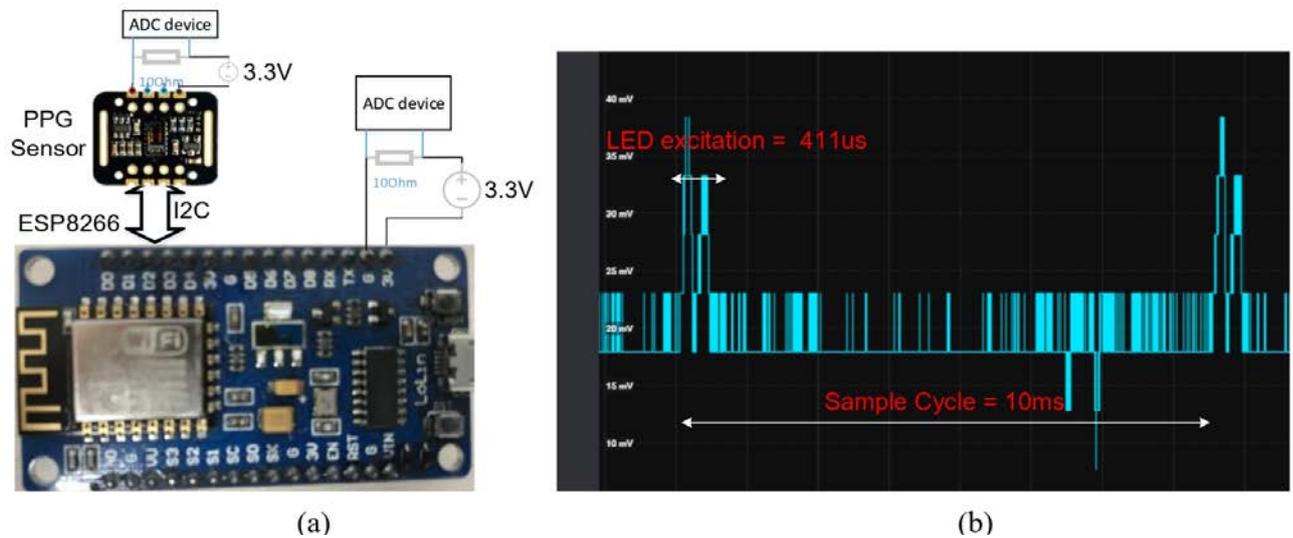
Figure 7 (a) Current measurement model, (b) The current waveform of PPG sensor during acquire data (the voltage displays real current through 10Ohm resistor V=I*10)

Table 4 The comparison current consumption of PPG device with different mode.

Mode	Current (mA)	
	PPG sensor	PPG device
Sleep	0.5	x
Active	3.2	x
UART data transfer	x	23
MQTT data transfer	x	145

4.4. Evaluate the performance of signal compression with a real-time system

The second case studied is a real-time PPG measurement system, which is illustrated in Fig. 9. The main parts of PPG device contain two parts as ESP8266 and PPG sensor (MAX30102) which can change the sampling frequency as 100 Hz, 200 Hz, and 400 Hz. To remove the noise from the original PPG signal, we applied the low-pass filter follows the structure as: FIR (Equiripple, Fpass: 15 Hz, Fstop: 20 Hz)[36, 37]. For each experiment, the PPG system collect 2500 PPG samples to evaluate the compression method. The results describe in Fig. 9.

The compression ratio of the proposed method is highly dependent on the shape of PPG signal. In our tests, the highest CR was 271.2, with PPG signal at 200 Hz sampling frequency. This CR is really higher than previous studies [16, 22, 31-33]. The CR was reduced to 17.5 at the configured 100 Hz sampling frequency, and the distortion of the reconstruct PPG signal was relatively small. The CR was only 4,561 with distortion as 3.3% at 400 Hz sampling frequency. However, the shape of PPG signal was maintained quite accurately.
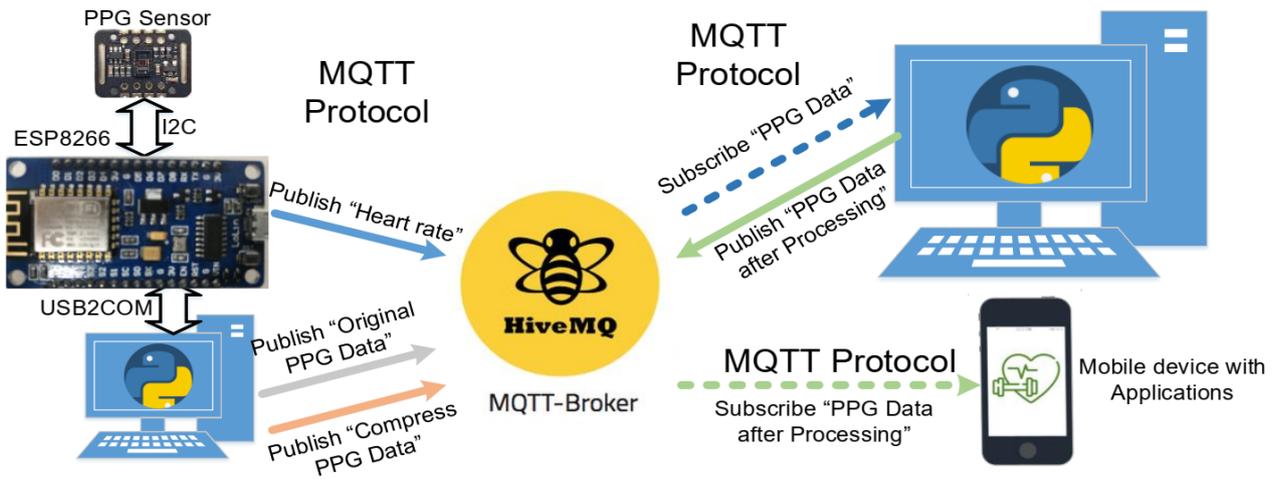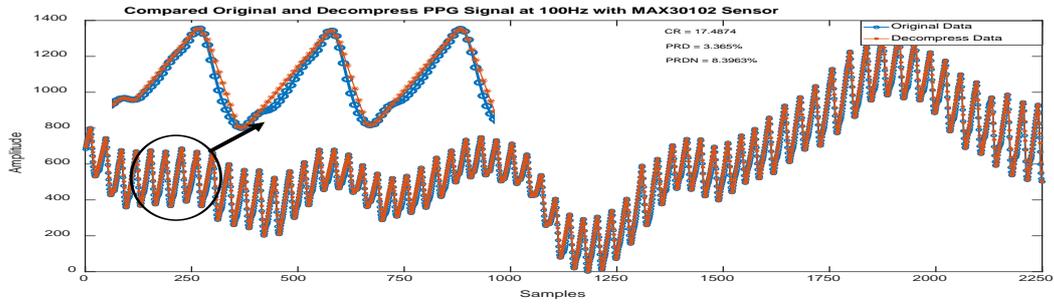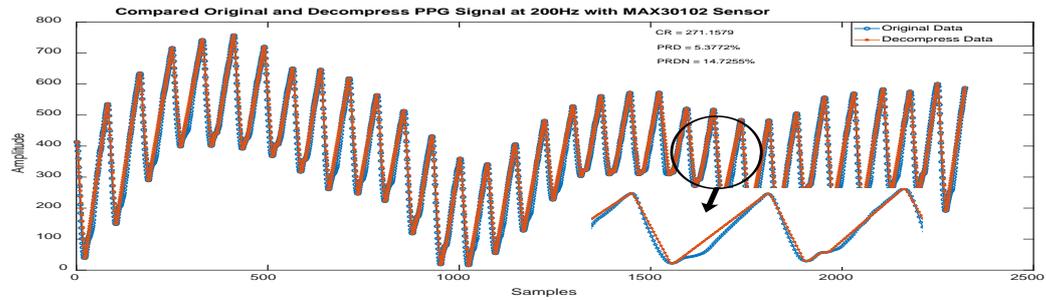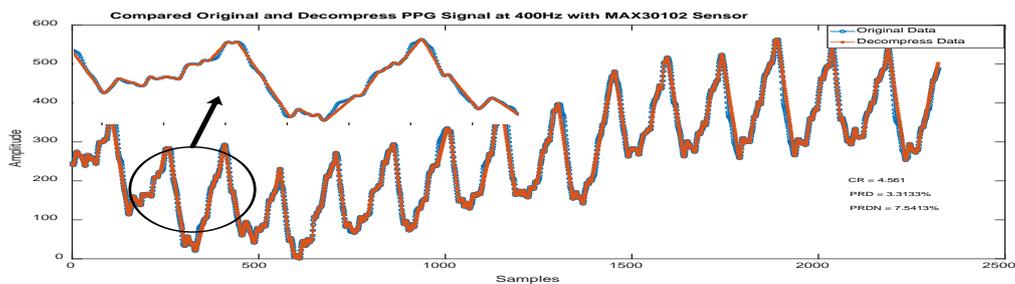
Figure 8 The proposed healthcare system with real-time PPG measurement

(a)

(b)

(c)

Figure 9 Compared the original and decompress PPG signal in real-time: (a) PPG measurement at 100 Hz, (b) PPG measurement at 200 Hz, (c) PPG measurement at 400 Hz.

5. Conclusions

This paper proposed compression method based on the characterization analysis of PPG signals combine with Huffman algorithm in the time domain. The highest CR of the proposed method is 387.8 at sampling frequency of 125 Hz. The main features of PPG signal are 2 points max and min and convex still retains with the reconstruct signal. The proposed heuristic rules with the first compression step is suitable with HR estimation application.

The value of CR directly depends on the shape of PPG signal that is suitable with the clean and smooth signal. To reduce the distortion of reconstruct signal, the deep learning algorithms need to use for achieving a more accurate signal.

However, the proposed heuristic rules for calculating HR do not require complicated calculations, but it uses directly data after the first step compression and still give high accurate results. These application use PPG signals to monitor body parameters and calculate HR for the elderly or patients on treatment. These applications often require long times monitoring with a high CR helps reduce memory usage) and a relatively clean PPG signal (heuristic rules effectively applied to calculate HR).

To select transfer PPG data via UART can be increase the battery life of device. The proposed PPG measurement system can be processing data in real-time and reduce the power consumption of PPG device without transfer data through WiFi. The high performance of PC can be processing the high-frequency PPG signal for evaluating details of PPG features. The proposed method opens the new application for PPG signal suitable for smart healthcare system.

Acknowledgements

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