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ORIGINAL ARTICLE

RP3MES: A Key to Minimize Infection Spreading

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Abstract

Healthcare facilities, especially in highly populated countries like India where patient to doctor ratio is very high, are under a huge burden. Thus, Remote Patient Physiological Parameter Monitoring using Embedded System (RP3MES) becomes essential to monitor a large number of people admitted in hospitals and also patients afflicted with infectious diseases. The design for RP3MES addresses the key issues of portability, cost-effectiveness, low power consumption, user-friendliness, high accuracy and remote communication to facilitate vital parameter(s), like heart rate and body temperature, measurements and emergency notification, keeping in mind, the health of the caregiver(s). ARM Cortex M3 embedded processor and low-cost sensors are used to achieve the cost-effectiveness and low power consumption. Alarming unit intimidates a remote caregiver regarding their patient's health condition. The accuracy of the system measured data is 99.4% compared with the gold standard, which has been verified using Lin's Concordance Correlation Coefficient and Bland–Altman analysis. A comparison of our system with other commercially available ones is also presented here. The proposed system has wireless connectivity which minimizes infection transmission among family members and caregivers of the patients. It may also reduce the burden on healthcare staffs in hospitals.

Keywords ARM Cortex M3 · Correlation · Micro-controllers · Public healthcare · Remote monitoring · Zigbee

Introduction

Keeping in mind India's current healthcare infrastructure of around 1.4 hospital beds per 1000 people of its population, which is unevenly distributed in the country, where existing bed capacity is mostly saturated in government hospitals (Kapoor et al. 2020). According to census 2001, there are 61.3 nurses and midwives per lakh population, out of which only 9.9%, i.e., 62,592 nurses have a medical qualification (Anand and Fan 2016), which indicates a huge shortage of trained healthcare workforce. Thus, there is a lot of pressure on these trained healthcare staff to monitor all the in-hospital patients regularly. There are also chances of the nursing staffs or caregivers getting infected from any patient suffering from communicable diseases, rendering them incapable of providing further services. The current pandemic has taught us that personal protection is utmost important for the caregiver(s) of any patient suffering from Anthroponoses (human-to-human transmitted diseases). This dire need has driven us to aim for remote patient physiological parameter monitoring using embedded system (RP3MES) where we have designed, implemented and analyzed a low power, accurate, cost-effective and user-friendly remote health monitoring system. In this paper, we describe the design of an ARM Cortex M3 embedded processor based system which will be beneficial for remotely monitoring the physiological parameters of patients, mainly in-hospital and home-based patients or elderly persons living alone, and analyze the performance of this proposed system using Bland–Altman curve and Concordance Correlation Coefficient.

S. Das et al. have developed a robust photoplethysmography (PPG) based real-time heart rate measurement technique (Das et al. 2016) using an Arduino Uno board. However, this system can handle a limited amount of data because of the low memory of an Arduino Uno micro-controller and may crash when simultaneously multiple programs are run or large data is handled. A. B. Hertzman in his paper has proved the utility of PPG measured from the fingers

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and toes in man (Hertzman 1937). Its application in clinical physiological measurement has further been established by Allen (2007). It has also been verified that PPG-based heart rate monitoring has many advantages over traditional Electrocardiogram (ECG) methods (Zhang 2015). Motion artifacts (MA) are major contributors to noise in a PPG signal. They arise due to physical activities of the person whose PPG signal is being measured and can adversely affect the heartbeat count. State-of-art technologies are used to minimize MA in PPG signals (Puranik and Morales 2019; Chen et al. 2018; Tseng et al. 2015; Ram et al. 2012). However, we are interested in measuring the resting heart rate of a person, so, MA is not a concern in our sensor design. Considering the pros and cons of PPG sensors over traditional ECG-based sensors for heart rate monitoring, we have chosen PPG-based sensors for measuring the resting heart rate of a patient, which makes hardware implementation of the system simple, cost-effective and requiring lesser power. A. Leone et al. proposed a prototype Temp100 sensor-based vital sign monitoring system using near field communication (NFC) to ensure security, low power consumption and cost-effectiveness (Leone et al. 2015). In their work, NFC has up to 10 cm range which defeats our purpose of keeping at least 1 m physical distance with the care-giving family member. L. Yu et al. have designed a Hong Kong-based health monitoring system that caters to the needs of elderly people (Yu et al. 2018). This sophisticated health monitoring system is expensive and is not affordable by an average Indian family for their home-based patient. An online real-time health monitoring system dedicated to constantly monitor and send data to a server via General Packet Radio Service (GPRS) (Patil and Hogade 2012) is not ideal as a medical staff must continuously monitor these uploaded data for any abnormalities. The system is not capable of interpreting an emergency based on these measured data and hence fail to generate an alarm.

The authors in this paper have addressed the two most important key issues of the healthcare system—cost and accuracy. We have considered the issues of cost because it imposes a financial burden to the family, hospitals and ultimately the government to install expensive and high-end devices to monitor vital parameters and accuracy which is crucial for the patient's safety and the proper amount of medical attention received by him/her. So, instead of using market available sensors, we have designed the sensor modules of our system which reduces the overall system cost. The system performance has been judged using Bland–Altman analysis and Lin's Concordance Correlation Coefficient and achieved 99.4% accuracy. The proposed system has provisions of raising an alarm and also notifying the immediate caregiver, situated within 100 m indoors, wirelessly using Zigbee protocol.

The significant features of our work lie in the following aspects of the proposed system:

1. Self-designed low-cost sensors, having low power consumption, with 99.4% accuracy are used to measure the vital parameters.
2. Local LCD help the doctors to monitor the patient's vital parameters during every visit.
3. Alarm Unit helps to indicate any abnormality in the patient's vital parameters.
4. To avoid the risk of infection transmission to other family members, a Zigbee remote communication module helps to send the patient's vital signs data to the immediate caregiver monitoring with a central Zigbee receiver module/hub up to a range of 75–100 m (indoors).
5. Up to 6500 Zigbee nodes can be integrated into a central hub making it possible for even a single person to monitor a huge number of patients simultaneously from a safe physical distance.

Thus, the main novelty of our proposed system is that it can mitigate the problem of healthcare staff shortage that India faces under this pandemic situation and also minimizes the spreading of infection.

The rest of the paper is organized as follows: Section "System Architecture" presents the system architecture of our proposed remote patient physiological parameter monitoring system. The methodology of our system with the experimental arrangement, collection and statistical analysis of the data is described in Section "Methodology". Section "Results and Discussions" displays the results of the measured vital signs of the volunteers compared with the gold standard measurement and the performance analysis of the system is manifested in tables and plots. Finally, the paper is concluded in Section "Conclusion".

System Architecture

The proposed system can measure two vital parameters—heart rate [in beats per minute (bpm)] and body temperature [in °C and °F]. It comprises four sections— Input Section, Embedded Processor Section, Output Section and Remote Communication Section. Figure 1 represents the overall layout of our system.

Input Section

The input section of our system is designed for acquiring and conditioning the patient physiological parameters (PPP) like heart rate and surface body temperature.

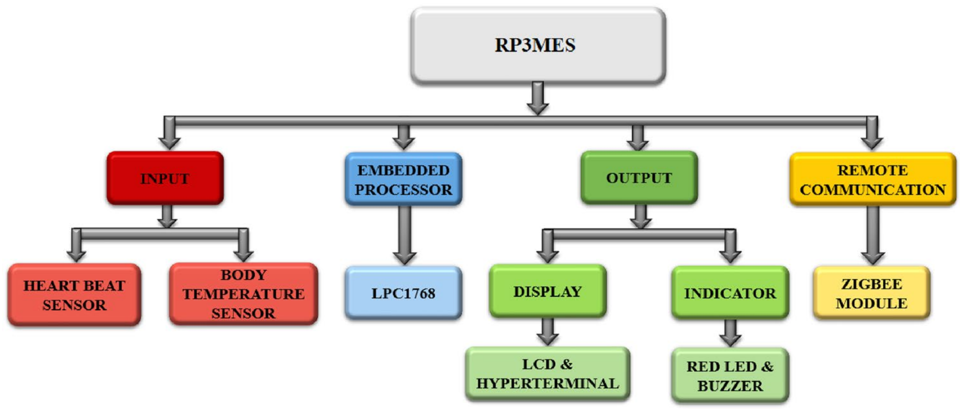

Fig. 1 The overall layout for Remote Patient Physiological Parameter Monitoring using Embedded System (RP3MES)

Heart Rate Sensor

We have designed our heart rate sensor based on the principle of reflective photoplethysmography (rPPG), which gives better reading than transmission PPG (tPPG) (Nijboer et al. 1981). The clinical acceptance and feasibility of PPG signals have already been established in the biomedical field by Allen (2007) and Hu et al. (2008). The measurements have been taken from the fingertip non-invasively. The proposed heart rate sensor module consists of three units: Optical sensor unit, Signal conditioning unit and Comparator unit. The detailed circuit description is elaborately discussed in one of our previous works (Ghosh et al. 2020).

A non-coherent infrared (IR) signal (from a low-cost optical sensor with low power consumption, placed below the fingertip) penetrates the skin and enters the bloodstream flowing through the arteries. During the ventricular systolic phase of the heart cycle, the oxygenated blood rushes to the arteries which absorbs a large amount of IR signal. This results in a sharp fall in the amount of reflected IR signal received by the phototransistor. Thus, a weak pulsatile ac is obtained at the output of the optical sensor superposed on a large dc signal. Each such pulse corresponds to one heart cycle and represents one heartbeat.

The rPPG signal sensed by the optical sensor is weak and noisy, so it is passed through a signal conditioning circuit comprising a two-stage active band-pass filter (BPF) and a voltage comparator circuit. The BPF is used to eliminate the dc component of the sensed rPPG signal (due to ambient light, IR reflected from the skin instead of the blood, etc.) and to amplify the ac component (due to arterial pulsation). The voltage comparator circuit converts the rPPG pulses to a square waveform of 0–3.3 V, which is the maximum input voltage for the Analog-to-Digital Converter (ADC) of the embedded processor ARM Cortex M3. Thus, each square pulse represents one heartbeat. The two stages of the BPF are identical, and it comprises a passive high pass filter (HPF) and an active low pass filter (LPF), shown in Fig. 2.

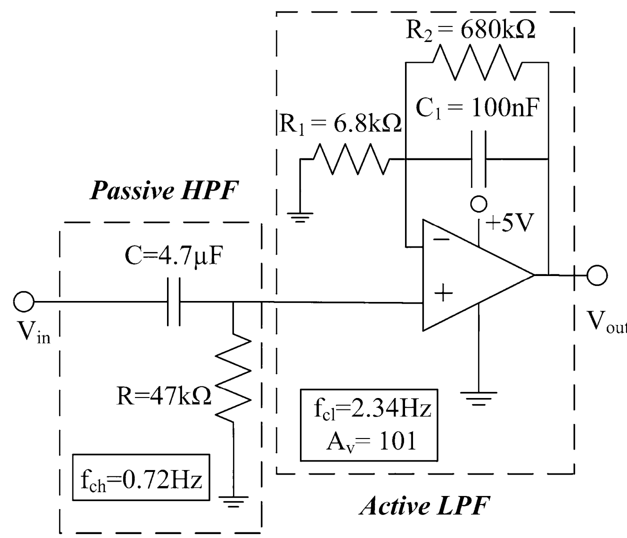

Fig. 2 The circuit diagram of a single stage of BPF of the proposed heart rate sensor

Table 1 Filter simulation data

Characteristic curve parameters	Values
Upper Stop-band Rejection Limit	2.60
Lower Stop-band Rejection Limit	0.65
Bandwidth Δf (in Hz)	1.95
Peak Gain G (in dB)	75.51
Resonance Frequency f_0 (in Hz)	1.32
Q-factor	0.68

The sensor is capable of reading the heartbeats of 43–140 bpm corresponding to a frequency range of 0.72–2.34 Hz.

The cascaded filter circuit is simulated in Tina-TI software to check its gain—frequency ac characteristic analysis curve. The simulation results are summarized in Table 1 and the graphs are shown in Fig. 3.

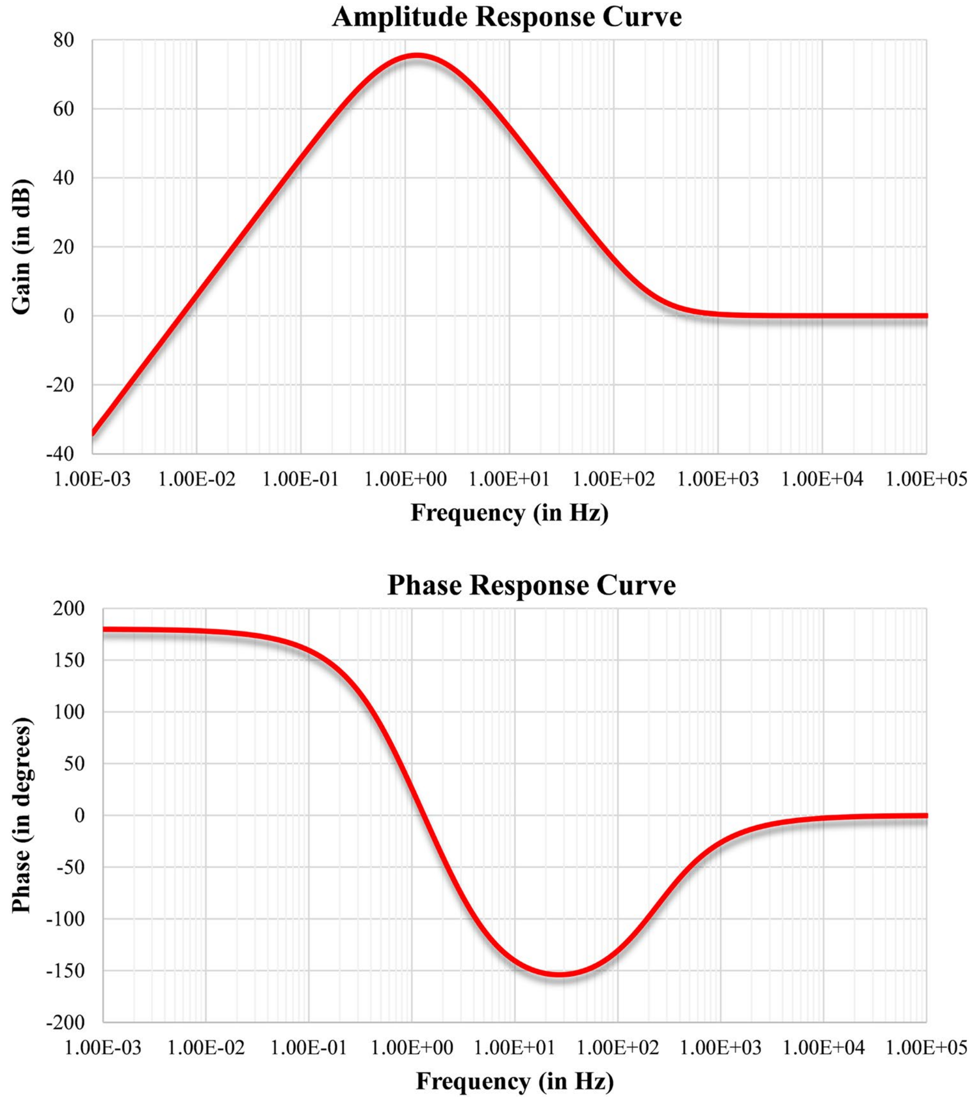

Fig. 3 Amplitude Response and Phase Response curves for the ac characteristics analysis plot for the filter circuit of our system

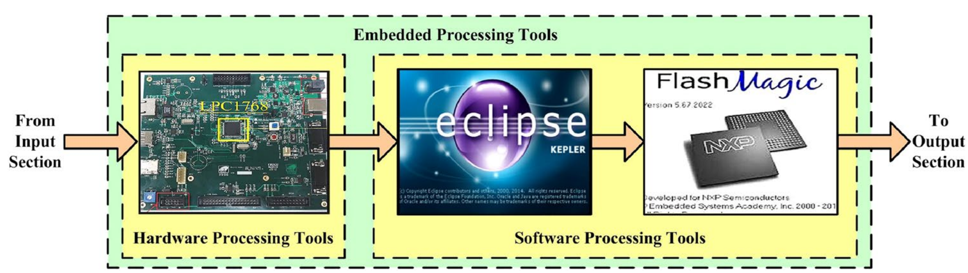

Fig. 4 The embedded processing tools used in our proposed system

Body Temperature Sensor

For measuring skin temperature of a person using our proposed system, we designed the surface body temperature sensor module using a low cost, low power temperature sensor. These circuit specifications can also be found in our earlier works (Ghosh et al. 2020). The measurements have been taken from the fingertip for our experimentation but can be wired into a probe-like arrangement to measure body temperature from the oral cavity, tympanic cavity or any other medically accepted body part (McCallum and Higgins 2012).

Embedded Processor Section

The embedded processor section comprises the different hardware and software tools (depicted in Fig. 4) which takes

Table 2 Comparison between AVR, ARM, 8051 and PIC Micro-controllers ElProCus (2021)

	8051	PIC[a]	AVR[b]	ARM[c]
Bus width	8-bit	8/16/32-bit	8/32-bit	32-bit/64-bit
Communication Protocols	UART, USART, SPI, I2C	PIC, UART, USART, LIN, CAN, Ethernet, SPI, I2S	UART, USART, SPI, I2C	UART, USART, LIN, I2C, SPI, CAN, USB, Ethernet, I2S, DSP, SAI, IrDA
Speed	12 Clock/cycle	4 Clock/cycle	1 clock/cycle	1 clock/cycle
Memory	ROM, SRAM, Flash	SRAM, FLASH	Flash, SRAM, EEPROM	Flash, SDRAM, EEPROM
ISA[d]	CLSC	Some feature of RISC	RISC	RISC
Memory Architecture	Harvard Architecture	Von Neumann Architecture	Modified	Modified Harvard Architecture
Power Consumption	Average	Low	Low	Low
Cost (as compared to features provide)	Very Low	Average	Average	Low
Other Feature(s)	Standard	Cheap	Cheap, effective	High speed operation

[a] Peripheral Interface Controller

[b] Advanced Virtual RISC (Reduced Instruction Set Computer)

[c] Advanced RISC Machines

[d] Instruction Set Architecture

the physiological parameters in raw form (electrical signals) from the input section and processes it to give the same parameters in a readable format to the output section.

Hardware Processing Tools

We have used the Educational Practice Board EPBLPC1768 (Edutech Learning Solutions Pvt. Ltd 2013), which uses an ARM Cortex M3 architecture based LPC1768 chip (Nxp Semiconductors 2016), as the hardware processor. The rationale for choosing the ARM Cortex M3 architecture are as follows:

1. It is one of the most cost-effective micro-controller architecture which provides faster operation compared to its other contemporaries.
2. It has a very good performance efficiency which allows it to do work without increasing power or frequency requirements.
3. It has very low power consumption which allows it to be a very good choice for making portable systems.
4. Programming can be done in a user friendly way in it.
5. Due to the properties of parallel processing and good memory capacity, the system does not crash even when a large number of peripherals are integrated with it.

A detailed comparison of the ARM architecture as compared to other contemporary micro-controllers is given below in Table 2.

Software Processing Tools

Eclipse Kepler 4.3 integrated development environment (IDE) handles the codes written in Embedded C programming language to produce a .hex file. This .hex file can be downloaded to the EPBLPC1768 board using Flash Magic so that the system can act as a stand-alone entity in future.

Output Section

The output section is used for displaying the measured health parameters in a readable format simultaneously on a 16×2 local Liquid Crystal Display (LCD) and a Hyperterminal console display.

To ensure alarming the caregiver in all cases of abnormal vital signs, an indicator circuit comprising two different alarms are used—optical (red LED) and acoustic (piezo-buzzer). Since the proposed system turns ON the alarm for only 2 s after each abnormal reading, it is not prone to alarming fatigue.

Remote Communication Section

Two Zigbee modules in the remote communication section are used to communicate the measured data to the remote caregiver for constant monitoring while maintaining physical distancing and notifying the caregivers in case of any abnormality in measured vital parameters. One Zigbee module attached to the patient's monitoring system acts as the transmitter while the other module with the remote caregiver acts as the receiver. In our proposed system, we have used the Tarang-P20 modules by Melange Systems (Melange Systems Pvt. Ltd 2011). These modules work in the ISM 2.4 GHz frequency band. The module requires 3.3–3.6 V dc power to run and has transmit power output and receiver sensitivity of 19 dBm and – 105 dBm respectively which makes it sufficient for our proposed system. The indoors communication range is 75–100 m (Zigbee Alliance 2020). Around 6500 Zigbee nodes can be simultaneously connected to a central hub making it possible to monitor a large number of patients by a single person. So, our system is a very good choice for patient monitoring in hospitals while handling a huge patient load with a limited number of trained healthcare staff.

The caregiver(s) can immediately inform a doctor regarding a patient's deteriorating health. Thus, the patient can get immediate medical attention that will be helpful in reducing the mortality rates in patients.

The LPC1768 micro-controller has up to 512 kB on-chip flash memory usable for code and data storage. The EPBLPC1768 also has provisions for a micro-SD (Secure Digital) card and a USB (Universal Serial Bus) device/OTG (On-The-Go). However, the proposed system displays and communicates data in real-time without storing them. In case the caregiver or hospital staff want to store them, they can easily collect these data from the Zigbee receiver hub/node and store in any desired server.

Methodology

Experimental Set-up & Workflow of the Proposed System

The experimental set-up for our proposed system is displayed in Fig. 5. The Zigbee receiver module at the remote caregiver end used for remotely monitoring the patient is shown in Fig. 6. The process steps for the entire workflow of our proposed system is given below in Algorithm 1:

Algorithm 1 Workflow of our proposed system

Initialize the system;
Initialize the Zigbee communication link;
Wait for 6s; % To stabilize the rPPG signals received initially from the fingertip %
repeat
    Read the Heart Rate Sensor's output;
    Count the trailing ends of pulses for 15 s in counter h;
    Calculate heart rate (in bpm) as $HR = hX4$;
    Display the value of HR in bpm on the local LCD and Hyperterminal console;
    Send the value of HR to the Zigbee Receiver module/hub;
    if $HR < 60 \,\&\, HR > 100$ [23] **then**
        Turn ON the Indicator for 2 s;
    else
        Wait for 2 s;
    end if
    Read the Body Temperature Sensor's output;
    Store the body temperature data (in ^{0}C) in counter t;
    Calculate body temperature (in ^{0}F) as: $T = \frac{9}{5}t + 32$;
    Display the value of both t in ^{0}C and T in ^{0}F on the local LCD and Hyperterminal console;
    Send the value of T to the Zigbee Receiver module/hub;
    if $T > 36.2\,^0C$ [24] **then**
        Turn ON the Indicator for 2 s;
    else
        Wait for 2 s;
    end if
until System is turned OFF

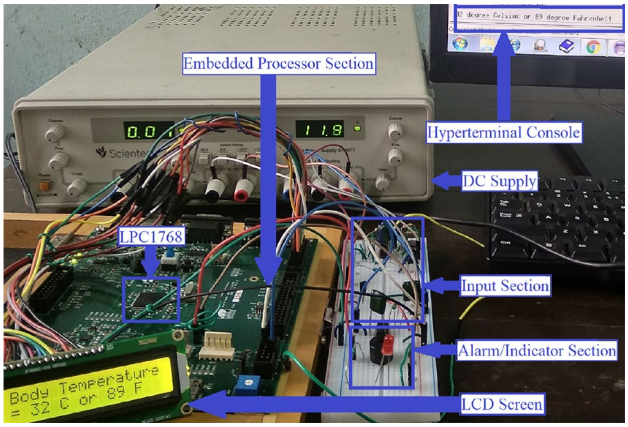

Fig. 5 Experimental set-up of our proposed system

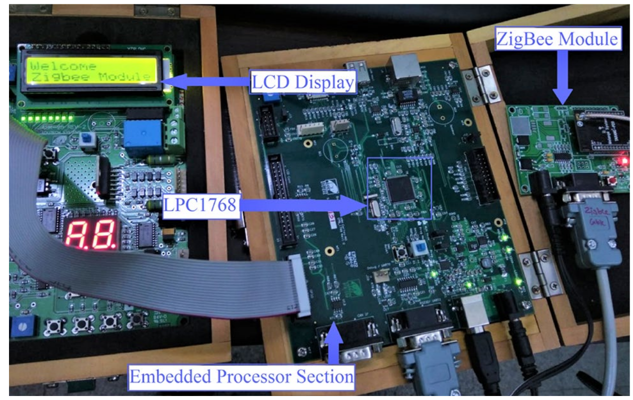

Fig. 6 Zigbee Receiver module at the remote caregiver end of the proposed remotely monitoring system

Data Collection

The heart rate and body temperature of 65 volunteers are tested by using our designed RP3MES. The demographics of the volunteers are listed in Table 3.

All the measured data are simultaneously validated by a registered medical practitioner, which was taken as the gold standard (GS). Manual readings of pulses from the radial artery are taken for heart rate validation, while the body temperature data is validated using a digital thermometer (pressed between the fingertips of forefinger and thumb) (Hicks 2018). The digital thermometer data is taken as the GS as it is clinically acceptable (Hicks 2018; Gerensea and Murugan 2016). Figures 7 and 8 shows the data collection process of a male volunteer both using our proposed RP3MES and by following the GS measurement procedure respectively.

The system is capable of measuring the resting heart rate, i.e., either in lying position or calmly sitting position, without any vigorous physical activities in the last 10–15 min. For our data collection, we have measured the heart rate of the volunteers in resting condition (Mishra and Rath 2011), which implies that they are in a calm condition and sitting position (after 10 min rest). During the entire data collection, the ambient temperature varied within 32–34 °C.

Statistical Analysis

To validate the acceptance of the proposed system, the data collected from both the heart rate sensor and the body temperature sensor are compared with our GS (manual measurement by registered medical practitioners). This comparison is done by plotting Bland–Altman Agreement Curves (Bland and Altman 1986) and by calculating Lin's Concordance Correlation Coefficient (CCC) (Lin 1989). The utility of these analyses to estimate the agreement between two methods of measurement is already proved in clinical and statistical measurements (Bland and Altman 1986; Lin 1989; Lin et al. 2002).

Bland–Altman Analysis

Bland-Atman (BA) analysis has been done for all the data collected by our system to study the clinical acceptability of such data. The horizontal lines in the BA plot denotes the mean of the differences $\bar{d}$ (further called as mean or bias) and upper and lower Limits of Agreement (LoA). Both the LoAs represent the range around the mean error value, within which, the difference between the measurements by both the methods for 95% pairs of future measured data lies (Bland and Altman 2007). All the analysis data are calculated with a 95% Confidence Interval (CI), i.e., 95% of the future measurements' data will lie within this interval for any specific parameter like mean or upper or lower LoAs. These are calculated using the mean, standard deviation of the differences (SD), *t*-value of the distribution (*t*) [assuming 2-tailed normal distribution] and sample size (*n*) as follows Bland and Altman (1986); Carkeet (2015):

$$\text{Mean}\bar{d} = \frac{1}{n}\Sigma(\text{Proposed System Data} - \text{GS Data}) \quad (1)$$

$$\text{Lower LoA} = \bar{d} - 1.96 \times \text{SD} \quad (2)$$

$$\text{Upper LoA} = \bar{d} + 1.96 \times \text{SD} \quad (3)$$

Table 3 Demographics of volunteers participating in the Vital Sign Measurement using our system

	Heart rate measurement		Body temperature measurement	
Sex	Male	Female	Male	Female
Number[a]	35 (63.64%)	20 (36.36%)	7 (70%)	3 (30%)
Age				
Mean	28.71 years	26.25 years	30.57 years	33.67 years
SD	8.91 years	5.23 years	10.10 years	10.60 years
Skewness	1.42	2.83	1.08	0.69
Minimum	20 years	23 years	20 years	24 years
Maximum	52 years	45 years	48 years	45 years

[a]The data has been collected on different dates but under similar environmental conditions, during the same month of the year. All the volunteers involved here are the students or professors or technical and non-technical staff of the Department of Radio Physics and Electronics, University of Calcutta. Body temperature analysis was done only in 10 patients whereas heart rate was done for 50 subjects. Body temperature measurement is a simple process and even with age and sex variations, it was showing a stable reading for all the volunteers. So, lesser number of samples were taken. However, the heart rate varied for each and every person and was also found to be affected by various factors, like, the heart health, age, sex, etc. of the volunteer. So, comparatively a lot more volunteers were considered to get an unbiased analysis of our heart rate monitor. Hence, different groups and numbers of volunteers participated for the data collection for vital signs measurement using our proposed system

$$95\%\ \text{CI of Mean} = \bar{d} \pm t\frac{\text{SD}}{\sqrt{n}} \tag{4}$$

$$95\%\ \text{CI of Lower LoA} = \text{Lower LoA} \pm t\sqrt{2.92}\frac{\text{SD}}{\sqrt{n}} \tag{5}$$

$$95\%\ \text{CI of Upper LoA} = \text{Upper LoA} \pm t\sqrt{2.92}\frac{\text{SD}}{\sqrt{n}}. \tag{6}$$

Lin's Concordance Correlation Coefficient

The Pearson's correlation coefficient (ρ) measures only a linear relationship between the collected data and the GS (gold standard/reference) data rather than any deviation from the 45° line. However, in a graph of collected data versus the GS data, the **perfect correlation** is depicted by not only a *linear relationship* but also by the *slope/inclination* of the said straight line. When the inclination of the straight line (which shows a correlation between the GS and the collected data) with the horizontal becomes 45°, the collected data perfectly agree with the GS data without a bias towards either of them. In mathematical terms, the correlation coefficient becomes a perfect 1.00.

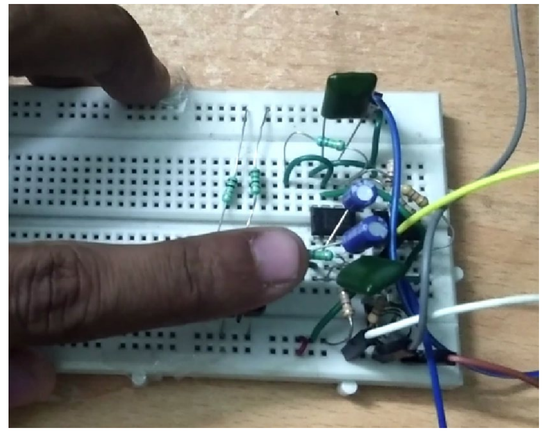

Fig. 7 HR measurement of a male volunteer using the proposed RP3MES

Fig. 8 HR measurement of a male volunteer using the GS procedure, for verification purpose

Lin's Concordance Correlation Coefficient (CCC) (ρ_c) can measure the agreement between the data collected and the GS data by measuring the deviation from the Concordance Line, i.e., the 45° line passing through the origin (Lin 1989). Thus, CCC is used, in this work, as a measurement metrics to judge the performance of our proposed sensors.

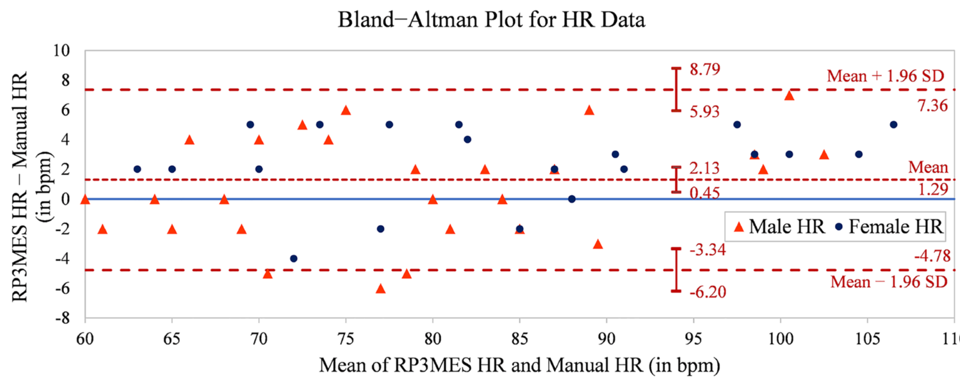

Fig. 9 Bland–Altman plot for the HR data, with the solid blue line representing the zero difference level, the finely dashed red line representing the mean $\bar{d}$, the boldly dashed red lines representing the upper and lower LoAs and their corresponding whiskers representing their respective 95% CI limits

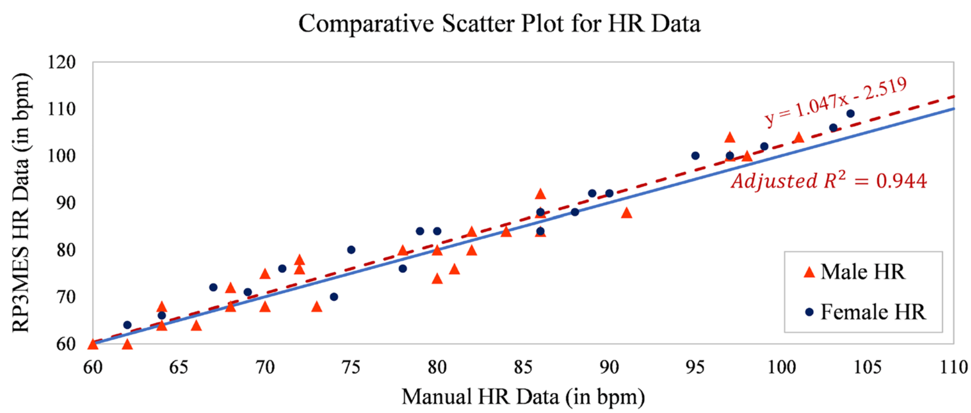

Fig. 10 The comparative plot of the HR data measured from our system versus the GS (manual) data, with the dotted line representing the regression line in comparison to the solid 45° Concordance Line

The accuracy and precision for measurement can be given in terms of the Pearson's correlation coefficient (ρ) and the Bias Correction Factor (C_b) by the Eqs. (7) and (8) respectively (Lin 1989; Lin et al. 2002). Thus, ρ gives a measure of the closeness of all the data points to the best-fit line while C_b depicts the deviation of the best-fit line from the Concordance Line (Lin 1992).

$$\text{Measure of Precision} = \rho \tag{7}$$

$$\text{Measure of Accuracy } C_b = \frac{\rho_c}{\rho}. \tag{8}$$

Results and Discussions

Heart Rate Measurement Analysis

The Heart Rate (HR) data measured by our system is plotted in a Bland–Altman plot (Fig. 9), where the *Y*-axis represent the difference of the GS (manual) HR from our system's HR and the *X*-axis represent the mean of these two HR data. Figure 10 shows the deviation of the regression line for the HR data, plotted for our system measured data with the GS collected data, from the 45° line. The statistical analysis parameters and their values calculated using (1)–(8) is tabulated in Tables 4 and 5.

Body Temperature Measurement Analysis

The Bland–Altman difference versus mean plot for the body temperature (BT) data between our system's measured data and the manually measured digital thermometer data (GS) is shown in Fig. 11. The deviation of our system measured BT data from the GS data is depicted in Fig. 12. Table 4 and Table 5 contain the statistical analysis results for the BT measurement (calculated using (1)–(8)) using our proposed system.

Comparison of the Proposed Model

The American National Standard on "Cardiac Monitors, Heart Rate Meters and Alarms" by AAMI (Association for the Advancement of Medical Instrumentation) states that the allowable readout error while measuring heart rate should not be greater than ± 10% of the input rate or ± 5 bpm whichever is greater (Institute 2002). The proposed system measures accurately both the heart rate and body

Table 4 Statistical parameters for the Bland–Altman Analysis

Parameters	Heart rate (in bpm)		Body temperature (in °C)	
	Value	95% CI	Value	95% CI
Mean $\bar{d}$	1.29	0.45–2.13	– 0.22	– 0.39 to – 0.04
SD	3.10	–	0.24	–
t-value	2.00	–	2.26	–
Lower LoA	– 4.78	– 6.20 to – 3.34	– 0.70	– 1.00 to – 0.40
Upper LoA	7.36	5.93–8.79	0.26	– 0.04 to 0.56

Table 5 Comparison of performance of our proposed system with the Gold Standard

Parameters	Heart rate monitoring system	Body temperature monitoring system
CCC (ρ_c)	0.964	0.956
Precision (ρ)	0.970	0.962
Accuracy (C_b)	0.994	0.994
Adjusted R^2	0.944	0.916
Regression Line	$y = 1.047x - 2.519$	$y = 0.993x + 0.023$

temperature of a person which is clinically acceptable accuracy. Table 6 shows the comparison of our proposed system with commercially available sensing systems whose performance (at rest) have been analyzed in previous works of literature.

Conclusion

This paper presents a low cost, low power remote patient physiological parameter monitoring system which measures the physiological vital parameters accurately. The overall development cost of our proposed system is estimated to be less than \$ 65. However, on batch processing for mass production, the cost will be highly reduced and the system will become cost-effective. The processor of our system has low power consumption and can be run by a 9 V supply. The system is an improvement over many commercially available sensor systems (Table 6) at a reasonable cost. Our proposed system will be highly beneficial for in-hospital or

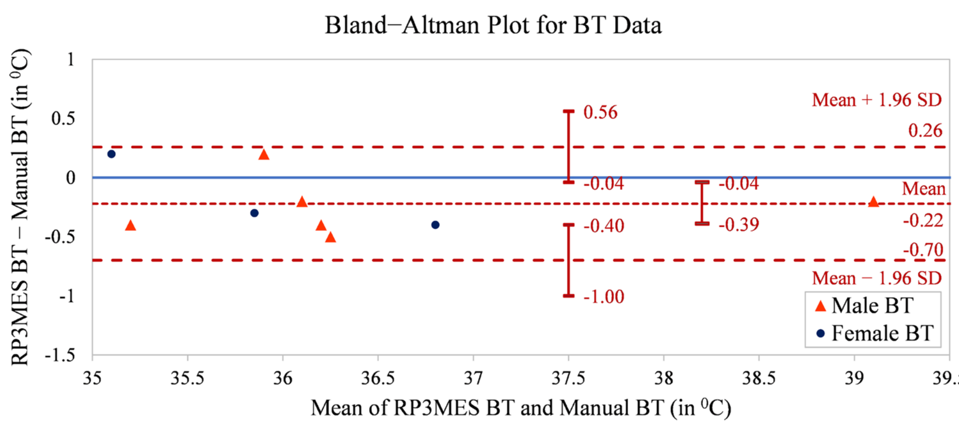

Fig. 11 Bland–Altman plot for the BT data, with the solid blue line representing the zero difference level, the finely dashed red line representing the mean $\bar{d}$, the boldly dashed red lines representing the upper and lower LoAs and their corresponding whiskers representing their respective 95% CI limits

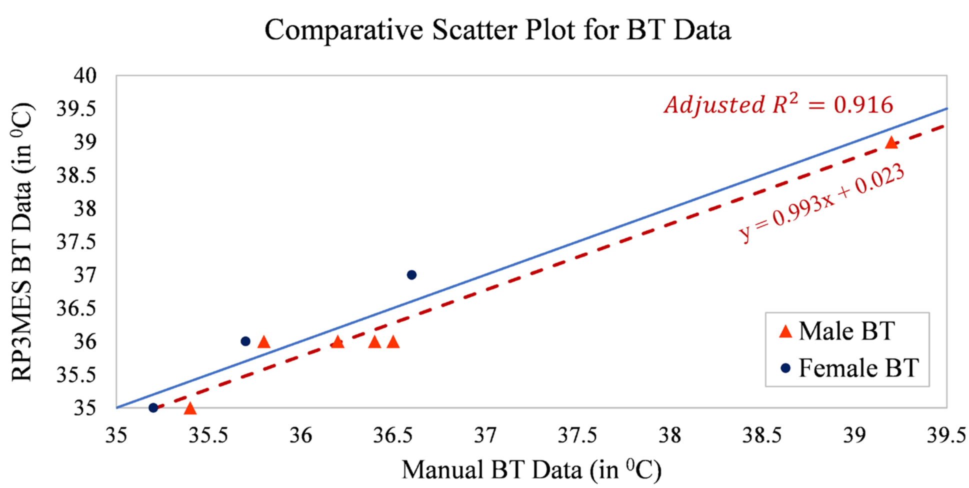

Fig. 12 The comparative plot of the BT data measured from our system versus the GS (manual) data, with the dotted line representing the regression line in comparison to the solid 45° Concordance Line

Table 6 Comparison of performance of our proposed system with Commercially Available Sensors as Analyzed by Previous Works of Literature

Sensors	Mean	LoA range (Limits)	CCC	Cost
Proposed System				< \$65[a]
HR Measurement	1.29 bpm	12.14 bpm (– 4.78 to 7.36 bpm)	0.964	
BT Measurement	– 0.22 °C	0.96 °C (– 0.70 to 0.26 °C)	0.956	
SensiumVitals[b] (Downey et al. 2019)				≈ \$44
HR Measurement	1.85 bpm	44.14 bpm (– 23.92 to 20.22 bpm)	–	
BT Measurement	0.82 °C	3.91 °C (– 1.13 to 2.78 °C)	–	
Basis Peak[b] (Cadmus-Bertram et al. 2017)	2.8 bpm	39.7 bpm (– 17.1 to 22.6 bpm)	–	≈ \$200
Fitbit Charge[b] (Cadmus-Bertram et al. 2017)	– 0.7 bpm	19.7 bpm (-10.5 to 9.26 bpm)	–	≈ \$91
Fitbit Surge[b] (Cadmus-Bertram et al. 2017)	– 0.3 bpm	9.6 bpm (– 5.1 to 4.5 bpm)	–	≈ \$230
Mio Fuse[b] (Cadmus-Bertram et al. 2017)	1.0 bpm	17.7 bpm (– 7.8 to 9.9 bpm)	–	≈ \$197
Fitbit Charge HR[b] (Kroll et al. 2016)	– 4.7 bpm	52 bpm (– 31 to 21 bpm)	–	≈ \$105
Apple Watch 3[b] (Nelson and Allen 2019)	– 2.47 bpm	28.95 bpm (– 16.94 to 12.01 bpm)	0.453	> \$280
Fitbit Charge 2[b] (Nelson and Allen 2019)	– 4.69 bpm	19.2 bpm (– 14.29 to 4.91 bpm)	0.561	≈ \$155
SensiumVitals[b] (Breteler et al. 2020)	1.0 bpm	31.3 bpm (– 14.6 to 16.7 bpm)	–	≈ \$44
HealthPatch[b] (Breteler et al. 2020)	1.3 bpm	11 bpm (– 4.1 to 6.9 bpm)	–	N/A
Non-Contact IR Thermometer[d] (Chen et al. 2020)	– 0.96 °C	3.47 °C (– 2.70 to 0.77 °C)	–	≈ \$10

[a]The estimated cost of our proposed system will be highly reduced on mass production

[b]System can also measure Respiration Rate (RR) whose parameters are not considered

[c]System cannot measure Body Temperature (BT)

[d]The work in this paper involves only Body Temperature analysis data, measurements being done from the wrist region

home-based patients (like COVID-19 or TB[1] patients), caregivers of home-based patients, medical staff in hospitals and also any person requiring constant vital sign monitoring (like elderly people). It can also be used regularly to monitor the PPPs and even warn the caregivers when their vital signs or PPPs indicate an unhealthy physical condition. These data are constantly communicated to a remote caregiver or medical staff via Zigbee communication for further medical help. The results of the BA and scatter plots clearly show that all the measured data points closely agree with the gold standard data. CCC value establishes that our system can monitor both heart rate and body temperature with 99.4% accuracy (compared to the GS) and has more than 96% measurement precision.

In our study we collected the vital signs data from healthy adults within the age group of 20–52 years, it can be equally effective for children, senior citizens or any other chronically infected patient. This is because the proposed system is not an illness/disease predictive system. The main aim of our system design is to measure the vital signs of a person and alert the caregiver whenever such measured value(s) is/are out of typical medically approved ranges. As our system does not require age and sex as inputs, our proposed system is independent of these demographics.

The work can further be extended by incorporating more low-cost sensors in system to monitor other vital signs like peripheral capillary oxygen saturation (SpO_2), ECG, Respiration Rate (RR) etc. for a complete hospital or home-based remote vital sign monitoring set-up. Integration of all modules in a single package of smaller size will make it easily portable. This work has potential application for communicable diseases like COVID-19, TB, influenza, etc. because it can minimize infection spreading by maintaining physical distance. The work has a scope to further extend in the field of a complete home-based remote health care management system by incorporating telemedicine and tele-ambulance services in this system.

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[1] Tuberculosis (TB), mainly the Multi Drug Resistant variety (MDR-TB), is known to affect hospital staffs, caregivers and family members Parmar et al. (2015).

Declarations

Conflict of Interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

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Ethics approval An Institutional Ethical Clearance Certificate has been issued by the Institutional Ethical Committee for Bio Medical and Health Research involving Human Participants, University of Calcutta for conducting this project.

Consent for publication The authors grant the Publisher an exclusive licence to publish the article, once accepted by the journal.

Availability of data and materials Real-time data is collected by our system which will be made available on request when the entire project is complete.

Code availability On request after the project is complete.

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