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Sensors Application in Remote Monitoring of Real-Time Healthcare Data using IoT

[1]Sadhana Mishra, [2]Bhupendra Dhakad, [3]Ranjeet Singh Tomar
[1, 2,3] Department of Electronics & Communication Engineering
([1]sadhanamishra.ec, [2]bhupendradhakad.ece, [3]ranjeetsingh)@itmuniversity.ac.in

ITM University, Gwalior

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Review/Article

ABSTRACT With increasing demand of remote healthcare monitoring, controlling, and prediction of diseases has been attracted researchers in the fields of sensor technology and Artificial Intelligence of Things (AIoT). Mainly, AIoT is the new paradigm which considers the real-time applications of Artificial Intelligence with Internet of Things. These AIoT applications also integrates different sensors with different IoT platforms for physical system design and emerged as a solution to remotely monitor the health of a patient by collecting real-time healthcare data through different sensor based intelligent Internet of Things (IoT) systems. Further, in remote healthcare systems, there is a growing demand of Non-Invasive Techniques for Real-Time measurement of vital signs such as Heart Rate (HR), Blood Pressure (BP), SPO2, Respiratory Rate, Blood volume associated to the Cardiac Pulse etc. Researchers are taking keen interest in Photoplethysmography (PPG) Signals acquisition, processing, and analysis to achieve contactless health monitoring. In this work, a novel system is proposed for remote monitoring of vital signs such as pulse rate which is analyzed through the real-time PPG signals collected at Things peak cloud platform. This proposed system can monitor heart rate, humidity and temperature parameters at the same time and these parameters can be visualized on the IoT based cloud platform. The proposed system contains pulse sensor, Temperature and Humidity sensor i.e., DHT11 which are integrated through IoT platform such as NODEMCU. Further, an algorithm is utilized to calculate Heart Rate from the PPG signal waveforms.

Keywords: PPG Signal Processing, Health Monitoring, Non-Invasive Techniques, Pulse Measurement, Peak Detection.

INTRODUCTION

Integrated approaches emerged as a solution to remotely monitor the health of a patient by collecting real-time healthcare data. Thrust areas such as sensor technology, IoT, and Artificial Intelligence (AI) are basic building blocks to achieve this remote healthcare analysis, monitoring, controlling, and prediction of diseases.

*Corresponding Author: Sadhana Mishra
Email: sadhanamishra.ec@itmuniversity.ac.in
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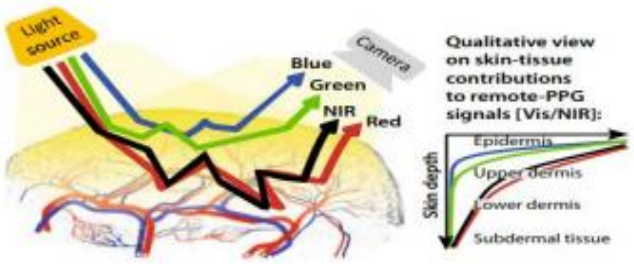


Figure 1: Generalized Representation of PPG Signal with Red, Green and Blue light signal waveforms [4]

The need for non-invasive methods for real-time vital sign measurement, including heart rate (HR), blood pressure (BP), SPO2, respiratory rate, blood volume related to the cardiac pulse, and pulse rate, is increasing as healthcare systems evolve.

In practical situations, PPG signals are collected from different body sites such as forehead, finger, wrist, arm, earlobe etc. The medical profession has seen tremendous and quick development in recent years in a number of areas, particularly in the area of remote healthcare system monitoring. These real time healthcare systems use sensors, actuators, edge devices and real time data with IoT to make lives easier for both patients as well as for doctors. These systems help doctor to treat or monitor the patient from far distances and reduce the time to travel to patient and it provides patient the facility to be treated by specialist doctor anywhere in the world in less time and with more accuracy with real time date of patients' health.

Non-invasive way is one of the major advantages of remote health monitoring as there is no need to be physically present at the hospital for testing, disease diagnosis and consultancy. Researchers have used the different biomedical signals such as ECG, EEG and Photoplethysmography (PPG) to measure the vital signs through non-invasively. Collection and acquisition of PPG signals non-invasively is simple, convenient, and economically efficient. In this approach, there is no contact with the skin whereas in plethysmograph skin contact is essential. PPG signal waveforms with red, green, blue signal waveforms are shown in Fig. 1 in which red and green signal waveforms are mostly considered for analysis of peaks in these waveforms and pulse rate and oxygen saturation levels are computed by applying an algorithm. It's an easy to collect the real time PPG datasets through smartphones, and wearable devices using sensors and IoT technology. In this respect, the proposed work is mainly focusing on real time data collection and applying an algorithm to calculate pulse rate, temperature and humidity parameters. PPG signals are one dimensional which can be generated through either PPG imaging or camera-based PPG and can be used in place of each other. Video signals from head, fingertips, and face are extracted and can be analyzed in time domain, frequency domain and different proposed algorithms are applied to calculate these vital signs. Further, proposed algorithms can be employed in any smartphone to monitor these parameters. Recently, AIoT systems support real time prediction of health parameters also via application of more advanced machine learning algorithms. Deep Learning models are also used to determine vital signs such as BP from video signals. PPG sensor can be designed using SMD 2420-001 Honeywell photodiode and SME 2470 Infra-Red (IR) emitting diode [1]. With the growing demand of Non-Invasive or Non-Contact Techniques in remote healthcare has emerged PPG signals exploration for AI based system.

This paper is organized in five sections. In Section II, background of non-invasive techniques is discussed. In Section III, overview of PPG signal generation, processing and analysis is presented. Section IV presents discussion of the proposed system model with experimental results. In last section conclusion is presented.

BACKGROUND OF NON-INVASIVE TECHNIQUES

The PPG signal mainly consist two components alternating current and direct current. These signals can be directly measured through some wearable devices and can be sent remotely on cloud platforms for analysis using IoT technology [2]. As reported in [3], the green PPG signal amplitudes are stronger in the 300-900nm wavelength than the red and NIR signal waveforms. Collecting the PPG signal through different techniques is easy compared to ECG. Further, researchers are exploring the PPG signals in AI review for automatic detection and prediction of heart diseases. Still there are challenges of insufficient dataset availability for PPG signals along with artefacts associated with the measurement of PPG signals [5]

In [6], a PPG sensor includes a light source which is exposed to the skin and reflected back signal is collected. The PPG signals red and NIR waves are utilized in figure-based measurement whereas in camera-based imaging green signal is used for analyzing the pulse rate heart rate oxygen saturation levels etc. PPG signals achieved through wearable wrist band, smart watches can be easily applied for monitoring lifestyle and environmental parameters which can lead to track and record individuals mental stress, sleeping disorder health issues [7]. Pre-processing of PPG signal is highly essential step to enhance the robustness of wearable devices which are extremely affected by motion artefacts. Recently PPG based healthcare and AI driven physiological signal analysis have gained significant important to assist wearables in healthcare systems. Researchers in [14-24] have explored non-contact PPG systems and wearables, HRV estimation, motion artifact reduction, neural networks, deep learning for biomedical signal analysis. Authors in [23-27] have focused on signal quality improvement, BP estimation, and sensor reliability by using CNN and Spectro temporal NNs. Further, in concern with remote monitoring IoT is another technology which is rapidly increasing for real tie data collection at cloud platforms, monitoring of activities, and real time controlling support AI-IoT is integration of AI/ML technology with IoT. In this context, Authors in [28-29] discussed real time data

monitoring and controlling whereas in [30-31] smart traffic management strategies are discussed with ML techniques. Moreover, GAN- based synthetic physiological signal generation, recurrent conditional GANs have been investigated for time series augmentation and AI enabled healthcare analytics [32-34].

OVERVIEW OF PPG SIGNAL GENERATION, PROCESSING AND ANALYSIS

This section discusses different PPG signal generation, processing, and analysis techniques. Monitoring of Pulse Rate, Heart Rate, SPO2, respiratory rate, and other clinical diseases are challenging in case of real time monitoring and processing because of intensive physical activity causes artifacts which directly or indirectly affects true estimation. Firstly, PPG signal generation is explored. Biomedical signal generation mainly requires input parameters from the body sight such as figure, wrist, head, etc. signal are obtained from optical devices. Blood volume and flow are measured by plethysmograph which measures the organ's volumetric change and results in heart beat count.

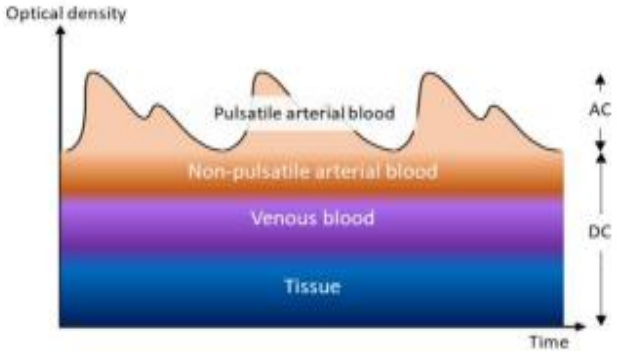


Figure 2: Representation of PPG signal AC and DC component [5]

As shown in Figure 2, PPG signal is composed of DC components and AC components where DC components are superimposed on the pulsating AC components. Pulsating AC component is obtained from cardiac blood volume variation whereas DC component is obtained from automatic sympathetic nervous system and respiration system and it is very low frequency component. Measurement of PPG signal can be acquired in two different modes one is transmission mode and the other is reflective mode. In chamber-plethysmography the volume change is converted into blood flow by using mathematics. However, to observe the pulsation rate of heart only relative volume is needed. In relative volume case is only timing information remains and not shape or amplitude. For processing the PPG signal along with acceleration signals time-frequency based algorithms exist in the literature though it's also a challenge to investigate different algorithms for best reconstruction of the PPG signal. Removals of motion-artifact and drift are also pre-processing technique. The electronic circuit can be designed to support biasing of LED, Photo-transistor or photo-diode then remove motion artifact and provide isolated pulses of heart beat. To filter out the motion artifacts pair of adaptive filters can be used. Hear Rate estimation with motion artifact is a great challenge in PPG signal processing. For processing this contaminated PPG signal de-noising techniques play important role to bring accurate measurement. Heart beat detection from PPG signal is a signal processing technique which involves number of proposed beat detection algorithms in the literature selection of the proper beat detection technique is still a challenging task. In [8], processing of heart rate estimation is discussed with proposed de-noising technique with inclusion of PPG signal acquired from sensors and body movement via accelerometer sensor signal in X-axis, Y-axis, Z-axis, i.e., in three dimensions are added with PPG. FFT tool of signal processing is essential to transform a signal from time domain into frequency domain to analyze the different parameters in frequency domain. Power distribution with frequency is calculated in the frequency domain with power spectral density of the signal. PPG signal analysis is carried out with the de-noising of the signal or attenuation of noise after de-noising the signal is analyzed in frequency domain to know the power variation with frequency. Digital filtering with adaptive filters in the frequency range 0.4 Hz to 3.5 Hz of [9] is considered for band-pass filter in frequency and then inverse FFT is applied to convert in time- domain. Z-score normalization and average are statistical parameters. After pre-processing next step is analysis in time domain to identify pulses, identify fiducial points in the pulses, features of the pulse, abnormal features of the pulse, identify abnormal pulses are analysis features of the PPG signal waveform. Feature extraction is essential component for monitoring and diagnosis of PPG signal. Frequency domain analysis is utilized for this purpose. Once the signal is in discrete time and discrete frequency components then Fast Fourier Transform (FFT) can be easily applied. Biomedical signals processing requires study and analysis of Finite Impulse Response filters. Some of the Infinite Impulse Response filters such as Chebyshev, Butterworth filter type I and type II, and Elliptical filters could be used for biological signals. Not only motion artifact even sudden breathing change can cause inaccurate measurement of heart rate. It is very essential to analyze PPG. Authors in [10-12] proposed the non-invasive techniques using PPG waveforms for

wearable healthcare systems to easily monitor health related parameters. In [12] authors have proposed blood pressure monitoring and analysis approaches which are contactless. Authors in [13] proposed glucose level monitoring with PPG signals and peak to peak detection is explored.

DISCUSSION OF EXPERIMENTAL RESULTS FOR PROPOSED SYSTEM OF PPG SIGNAL GENERATION AND MEASUREMENT OF VITAL SIGN

This section demonstrates some of the PPG signal waveforms for various stages of signal processing. Now it's very challenging to remove the noise from these signal waveforms and then process these signal waveforms for analyzing some physiological parameters or vital signs. In this paper only example waveforms are illustrated for practical systems these PPG signals are collected from the subjects with different sights and with different conditions then analysis is carried out to evaluate some parameters.

This section first discusses the proposed system technical design and components needed for real time monitoring of temperature, humidity and pulse rate parameters to provide good health conditions. Basically, volumetric changes of blood circulation are measured by PPG devices which are equipped with photo detector and light sources. The most commonly used body site is figure for capturing the PPG signal as it is reliable and convenient to measure the PPG signal.

In this work an open-source cloud which is Thingspeak is utilized to monitor and analyze the various parameters such as pulse rate captured through pulse sensor and real time humidity and temperature parameters where pulse sensor has been interfaced with ESP8266 NODEMCU development board and programmed using Arduino IDE software. Real-time data generated through the IoT device integrated with sensor will send these sensed parameters to the Thingspeak open-source cloud platform and then analysis of waveform will be done by MATLAB analysis tool. In future, these real time parameters can be aggregated and can be used with machine learning to predict healthcare signs.

Temperature Sensor: The temperature of the body and surroundings can be measured with this technological instrument. It determines how hot or chilly the body is. It oversees the data's real-time monitoring. Further, body site temperature parameter can also be taken into account. In Fig. 3, real-time monitoring of temperature is done where temperature is estimated at a particular time interval. It is representing the average room temperature of 31.9 degree Celsius. In Fig. 4, Real-time monitoring of humidity is demonstrated where humidity is estimated at a particular time interval. The average humidity recorded that time was 74 as shown in graph. Further, some more results of real time parameters are demonstrated in Fig. 5 and in Fig. 6 with parameters visualized on NODEMCU console.

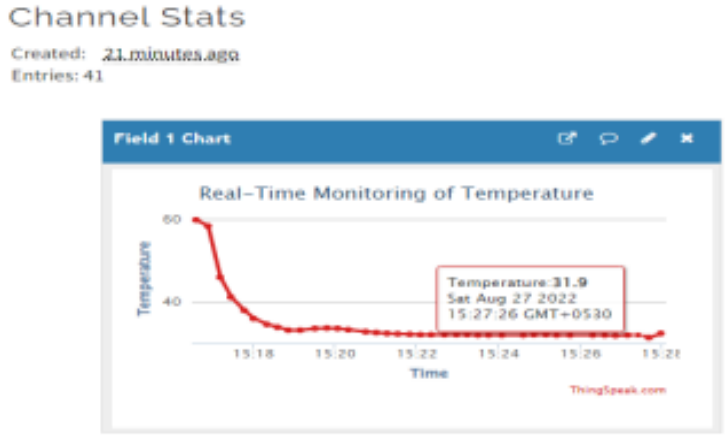


Figure 3: Real-Time Monitoring of Temperature on Thingspeak cloud platform

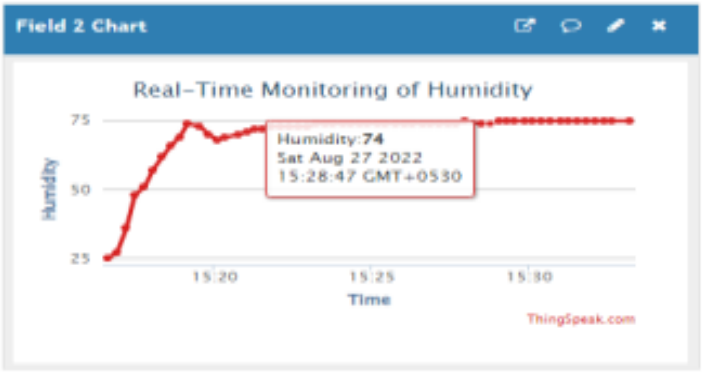


Figure 4: Real-Time Monitoring of Humidity on Thingspeak cloud platform



Figure 5: Real-Time Monitoring of Temperature and Humidity on Thingspeak cloud platform

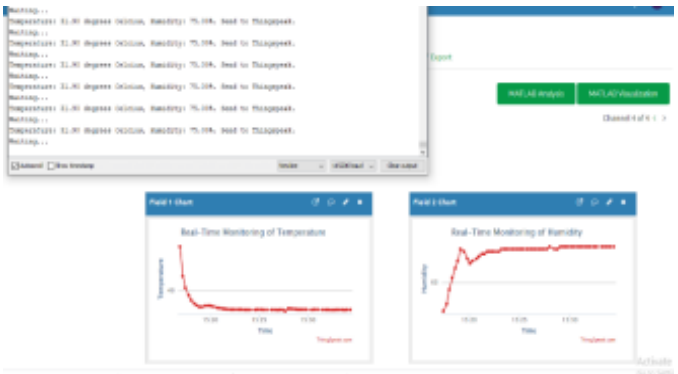


Figure 6: Real-Time Monitoring of Temperature and Humidity on Thingspeak cloud platform and NODEMCU output console



Figure 7: Real-Time Monitoring of Pulse Rate on Thingspeak cloud platform

In Fig. 7, pulse sensor is used to measure the pulse of a human being. This pulse sensor is a device which senses the changes in the blood volume this change in blood volume occurs when the heart pumps blood. Integration of pulse sensor and its coding is done to display the pulse rate on cloud platform which is ThingSpeak in this study. This pulse rate is measured in the unit of Beat per Minutes. When a finger is placed on this sensor it gives digital output which could be monitored on cloud as presented or on the console window of IDE. As shown in Fig. 7 the pulse rate is 71 pulse per minute (PPM) at specific time and time series representation is for continuous time.

Further, PPG Signals are demonstrated in Figures 8-10, represent the PPG signal generated for sampling frequency of 100Hz for varying number of samples ranging from 0 to 3000. From these total numbers of samples extracted PPG signal is presented in Figure 10 for the 400 to 1800 extracted number of samples. Mainly, these PPG signals are used to detect peak to peak interval which is mathematically used to calculate heart rate in algorithms. Demonstration of the peaks in Figure 11 is given through red circles in the waveforms.

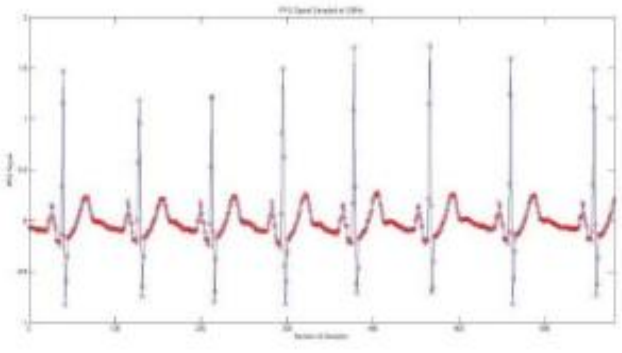


Figure 8: Representation of PPG signal with number of sample at sampling frequency 100Hz

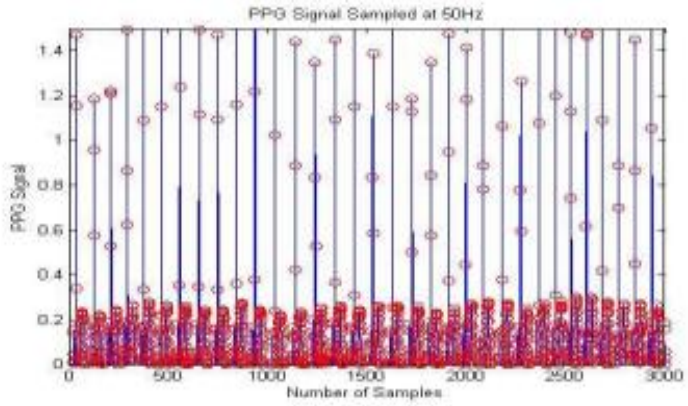


Figure 9: Representation of PPG signal with number of samples at sampling frequency 50Hz

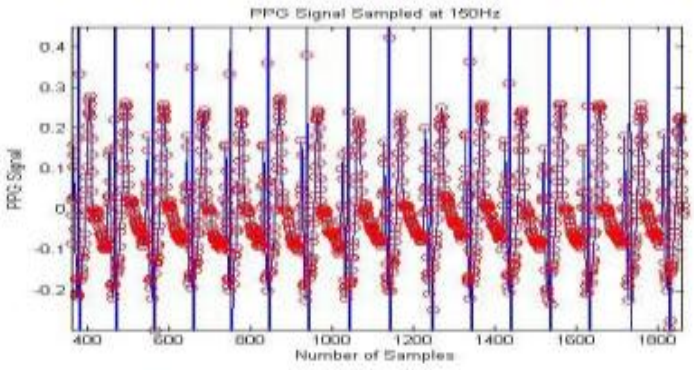


Figure 10: Representation of extracted PPG signal for 400 to 1800 number of samples at sampling frequency 150Hz

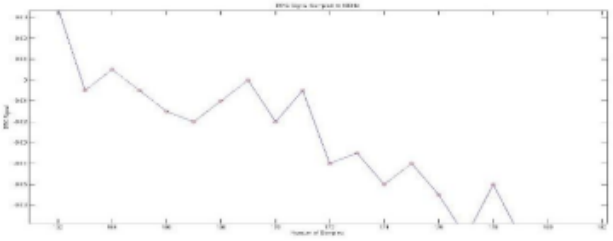


Figure 11: Representation of peaks in PPG signal with number of samples at sampling frequency 100Hz

CONCLUSION

In this work, the proposed system is utilized for remote monitoring of physiological indicators such as pulse rate which is analyzed through the real-time PPG signals collected at Thingspeak open-source cloud platform. This proposed system is designed using ESP8266 NODEMCU along with pulse sensor and Digital Temperature and Humidity sensor DHT 11 which can monitor heart rate, humidity and temperature parameters at the same time and these parameters can be visualized on the IoT based cloud platform. Further, this work can be extended by comparing the PPG signals collecting through two different proposed systems and vital signs can be analyzed. In future, advanced machine learning approaches can be applied to propose AI enabled health monitoring systems.

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