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A Smart, Non-Invasive Framework for Continuous Health Monitoring with Integrated Threshold-Based Alerting

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Abstract: ***The increased demand for accurate, real-time, and cost-effective health monitoring, particularly in the aged, chronically ill, and postoperative patients, necessitates the development of intelligent, non-invasive, and continuous monitoring systems. Traditional hospital-based monitoring methods often are expensive, cumbersome, and less accessible during emergencies. In this study, the design and implementation of a Smart Non-Invasive Continuous Health Monitoring System, which allows obtaining physiological data in real time, interpreting it, and visualizing the results on the cloud, have been described. Biomedical sensors are integrated in the system to measure crucial parameters such as SpO, heart rate, and body temperature, and use a microprocessor-based single-board computer (SBC), preprocessing of data, encryption, and wireless transmission. SQLite local data buffering provides reliability as it avoids the loss of data during network interruptions. There is further enhancement in signal processing schemes, like adaptive filtering and peak detection accuracy. An alert system based on a set of thresholds is effective in alerting medical experts about unusual values in real time through the use of a secure HTTPS-connected cloud dashboard. Scalability and integration with AI-based analytics and wearables are possible through the modular architecture. Experimental validation has shown high levels of reliability, low latency, and a high level of concordance with reference clinical mechanisms, which is a cost-efficient and scalable IoMT-based healthcare system to achieve continuous remote monitoring.***

Keywords: Telemedicine, Real-Time Monitoring, Internet of Medical Things (IoMT), Embedded System, Signal Processing, Cloud Heathcare, Physiological Sensing

1. Introduction

The devices for monitoring multiple non-invasive parameters in a smart way has evolved with the Internet of Medical Things (IoMT) and the digital health technology which are not impacted by the hospital walls. Ongoing health surveillance through wearable and portable biomedical devices shows significant promise in improving clinical outcomes, particularly in chronic conditions, post-operative or elderly patients who require a consistent check-up [1–2].

The traditional health monitoring systems have still faced major weaknesses including limited processing, use of wired connectivity as well as lack of cloud integration [3-4]. These aspects limit real-time access of data, scalability and ability to provide timely medical intervention, especially in remote or resource-constrained regions. Besides, data security, energy-efficiency, and interoperability of systems are additional challenges that hinder the successful execution of solutions already in place.

This paper proposes an embedded health monitoring system based on a microprocessor that will be used to acquire physiological signals in real-time, filter these signals in an adaptive manner, and securely visualize them in the cloud. The system measures vital signs like heart rate, SpO 2 and body temperature using non-invasive biomedical sensors. The local data buffering increases reliability during network outages, and secure wireless communication safeguards patient information.

The proposed platform enables health practitioners to access the vital signs remotely in real-time since it combines edge-level processing with cloud connectivity, allowing for an immediate reaction to abnormal values. The approach is a combination of conventional hospital surveillance and new home-based healthcare, which is cost-efficient, scalable, and effective in terms of continuous remote management of patients.

2. Related Work

1) Limitations of MCU-Based Health Monitoring Systems

Over the past decade, several embedded health monitoring systems have been designed based on low-priced microcontroller units (MCUs) and basic wireless protocols [13]. Irrespective of the fact that these designs are useful in small-scale or single-parameter monitoring applications, the designs have a number of limitations, which restrain its use in continuous and real-time monitoring in medicine.

Traditional MCU-based systems are often limited in processing capacity and memory bandwidth to simultaneously acquire and analyze numerous of the biomedical signals they are used to monitor. In addition, the little support on the multitasking impedes the effective handling of the data sampling, filtering, and the wireless communication operations simultaneously. Various systems used wireless transmission of data using Bluetooth, GSM or GPRS modules [6-7].

Nevertheless, the models faced problems in the forms of poor data throughput, high latency and inadequate encryption that undermined the functionality of patient data as well as its safety. Furthermore, these systems were designed by majority using wired sensor interfaces and autonomous data logging, which is inapplicable in cloud-based techniques of real time visualization or remote access to patients. Thus, they failed to adequately address the needs of the current telemedicine, where the key factors are scalability, interoperability, and automation.

2) Recent Advancements and Existing Challenges

The latest studies demonstrate advantages of replacing old, Memory Control Unit (MCU)-based systems with microprocessor-based systems like BeagleBone Black, Raspberry PI and NVIDIA Jetson Nano that provide multi-tasking, improved processing power and enhanced communication protocols [8-10].

They offer the capability of multiple operations, such as the signal processing on the device, secure data encryption and cloud integration suitable for the large IoT-based medical applications. ThingSpeak, AWS IoT, and Google Cloud Healthcare API Cloud-based dashboards and IoT middleware platforms have revolutionized the process of managing healthcare data by allowing visualization of data in real-time, data analytics, and alerts.

Despite these advancements, there are significant problems. Many systems are still faced with problems of limited battery life, high power usage and system integration challenges between various sensors and systems. Proactive healthcare intervention is hampered by the lack of embedded artificial intelligence (AI) to make predictions. As a result, there is a strong demand of an optimized, low-power, secure and modular health monitoring system capable of real-time operation, adaptive signal processing, and smooth connection to a cloud-based system which is what the proposed system aims to accomplish.

3. System Architecture

1) Embedded Processing Unit

The system is primarily built on a microprocessor based Single Board Computer (SBC) running a lightweight Linux operating system. The SBC is capable of multitasking, fast data acquisition and communication, and also has integrated support of network stack, a feature not found in traditional microcontroller- based systems and makes it suitable for a real-time health monitoring system.

The main functions of the embedded system are:

a) Acquiring biomedical signals via I²C and GPIOs.
b) Performing signal processing and filtering.
c) Securing and bundling sensor readings.
d) Managing cloud communications from the dashboard.

Both Wi-Fi and Bluetooth can be used to on-board or off-board, to deliver versatile deployment in the home or health clinic environment. An operating environment based on Linux provides for the inclusion of advanced data analytics system, such as machine learning-based anomaly detection, in future versions.

2) Sensor Integration

The physiological sensing unit comprises miniaturized and low-power biomedical sensors for non-invasive, continuous monitoring of critical parameters.

a) Optical Sensor: It uses dual-wavelength (red and infrared) light emitting diode (LED) and the sensor measures the reflected signal to accurately calculate pulse rate and oxygen level. The sensor offers calibrated digital output, reducing a nalog noise and drift. Periodic averaging is employed to a void transient instabilities.
b) Temperature Sensor: Utilized integrated sensor precisely measures human body temperature. The sensor provides calibrated digital output with no analog noise or drift. To increase stability, readings are averaged regularly so as to not get affected by transient fluctuations.

This sensing module uses a modular design that promotes an ability to add biomedical sensors and facilitates the system scalability for multiparametric health monitoring in the future.

3) Local Storage and Processing

Gathered sensor signals are initially processed to f ilter out noise and artifacts to guarantee accurate parameter e xtraction. This includes bandpass filtering, moving average, and adaptive thresholding for improved accuracy. The filtered measurements are stored locally in an SQLite database, e nabling fault tolerance and avoiding loss of data during network outages. This also facilitates smooth integration with the cloud as soon as the network is reconnected, enabling secure and seamless data access for remote monitoring.

4) Cloud Integration

Processed data is securely stored at the cloud s erver via HTTPS (HTTP over SSL) communication, maintaining data privacy and security during data transfer. A user-defined web interface displays real-time patient vital signs, trend data, and a utomated real-time threshold-based system to notify of abnormal readings. Healthcare providers can securely monitor and access data remotely, allowing for timely action and effective management of patient care.

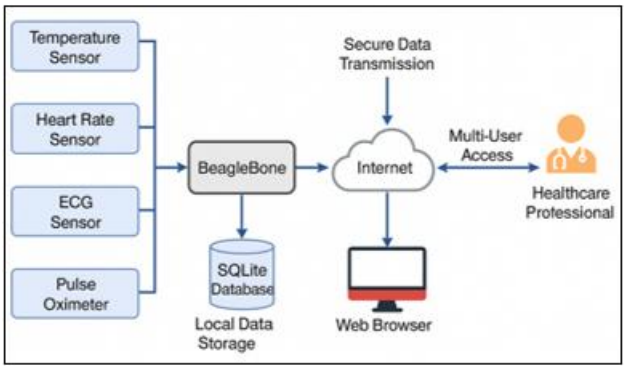

Figure 1: Block diagram and data flow of system

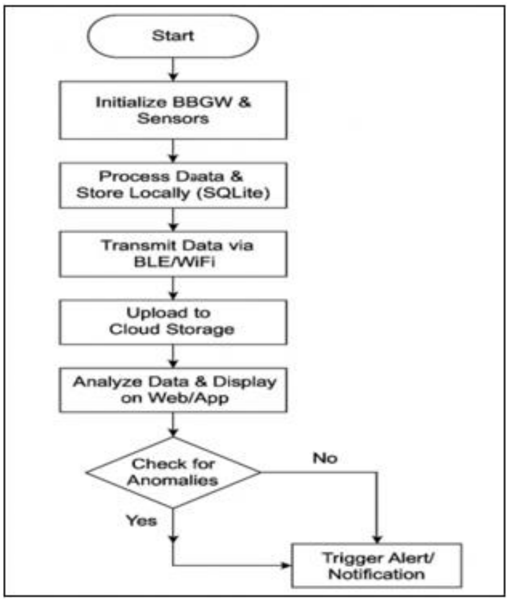

Figure 2: System flowchart including anomaly detection & notification

4. Computation of biomedical parameters

1) *Heart Rate Detection*

The first step in the processing of the photoplethysmography (PPG) signal is to apply a bandpass filter (0.5-4 Hz) to remove baseline wander and noise. This signal is then smoothed by applying a moving average low-pass filter. The peaks of the pulse wave are detected via adaptive thresholding. The RR intervals (time between peaks) are then used to calculate the heart rate (BPM or beats per minute) as:

$$HR = \frac{60}{RR_{Interval}\ (s)}$$

2) *SpO₂ Estimation*

Heart rate oxygen level is calculated using the ratio of-ratios method, which uses the AC (pulsatile) and DC (non-pulsatile) components of the red and infrared (IR) light signals.

$$R = \frac{(AC_{Red}/DC_{Red})}{(AC_{IR}/DC_{IR})}$$

$$SpO_2 = 110 - 25 \times R$$

This empirical formula offers a good estimate of the arterial oxygen saturation within physiological limits.

3) *Body Temperature Calculation*

The digital temperature sensor utilises the I²C i nterface and is a 16-bit calibrated sensor. The data i s converted from its raw form to degrees Celsius (°C) and then averaged to smooth out temporary variations to obtain consistent measurements.

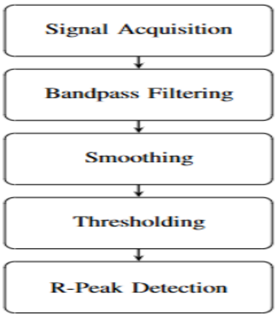

Figure 3: Heart Rate Detection Pipeline for PPG Signal

5. Results and Discussion

The Smart Non-Invasive Continuous Health Mon itoring system developed was evaluated in a laboratory setting on 10 subjects (22-58 years) with varied physical characteristics. Data from each subject were collected over a 60-second period at 1 Hz and the result was compared to another clinical device. Data readings were evaluated for accuracy, stability and reliability.

1) *Experimental Setup*

Participants were seated and rested to prevent motion artifacts. The optical PPG sensor was attached to the participant's fingertip to acquire heart rate and SpO, while a $_2$ digital temperature sensor was held against his/her wrist to record temperature. The data collected were locally processed by the SBC, and securely sent to the cloud dashboard for real-time display.

2) *Heart Rate Measurement*

The PPG sensor successfully measured pulse waveforms. Figure 4 shows the dynamic heart rate for one participant. The average system-measured heart rate for all subjects was 76.3 BPM, which is close to the clinical average of 75.8 BPM (with an average error of ±1.2%). This indicates that the peak detection and filtering algorithms used i n the signal processing phase were able to accurately identify peaks.

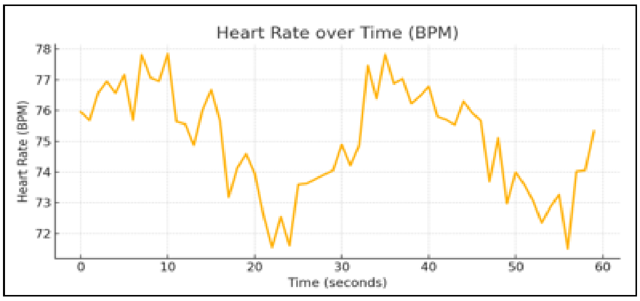

Figure 4: Heart rate over time (BPM) of a representative participant, showing reliable pulse waveform detection

3) *SpO₂ Estimation*

The SpO values were consistent during the test as demonstrated in Fig. 5. The average SpO levels $_2$ between 96.8% to 98.9% obtained from the system correlated well with pulse oximeters (97-99%). The mean absolute error (MAE) was 0.65% for the system, showing good accuracy of optical signal processing.

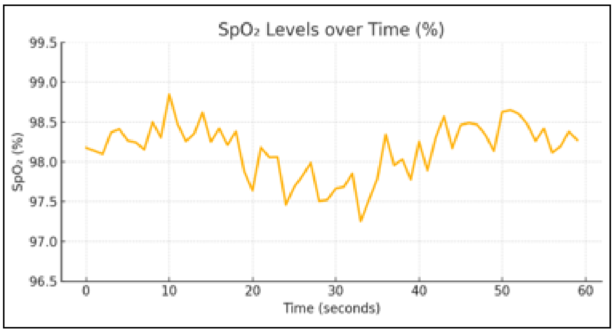

Figure 5: SpO_2 Levels over Time with correlated $_2$ oximeter readings

4) *Temperature Measurement*

Temperature measurements were stable for all subjects, and showed small variations from medical thermometers. As shown in Fig. 6, the measured range was 36.4 DegC, 36.8 DegC and the average offset was ±0.2 DegC. The low noise and stability of the digital sensor were achieved due to its I²C-based interface, and averaging algorithm.

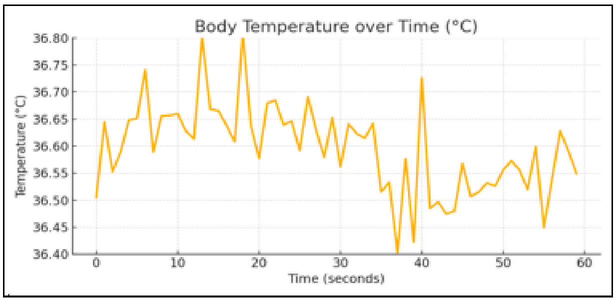

Figure 6: Measured body temperature (°C) vs. time, highlighting the robust signal-to-noise ratio of the sensing system.

A. *Overall System Evaluation*

Table 1: Overall system results

Parameter	System Avg	Ref. Avg.	Error (%)
HR(BPM)	76.3	75.8	1.2
SpO_2	97.9	98.3	0.65
Temp (°C)	36.6	36.7	0.2

The system demonstrated:
a) Low errors (less than 2%) in all vital signs.
b) Short latency (<250 ms) for data movement from acquisition to the cloud.
c) Up data does not get lost due to buffering in SQLite.
d) Robust performance with prolonged monitoring times.

This confirms the system's robustness, accuracy and feasibility of continuous health monitoring for homecare and other clinical settings.

6. Future Scope

The proposed Smart Non-Invasive Continuous Health Monitoring System has been successfully designed and tested for vital signs, such as heart rate, SpO, and body temperature. Nevertheless, certain modules shown in the system block diagram, including the Electrocardiogram (ECG) sensor unit, were not included in the present prototype owing to hardware limitations and project scope. The incorporation of an ECG module is planned for future development to provide direct heart rhythm monitoring, therefore substantially improving the system's diagnostic capabilities.

In the next phase, the system will be expanded to include:
- ECG signal acquisition and processing, allowing detection of arrhythmias and other cardiac abnormalities.
- Low-power optimization and wearable design improvements for long-duration patient use.

The next version of this platform will include an ECG module and improve system intelligence to offer a multi-parameter IoMT-based health monitoring solution for hospital and home care.

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