Sensor System for Research and Analysis of the Health State of the Organism

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Abstract

This article presents the development of an intelligent sensor system for monitoring and analyzing the health status of the human body. The system includes multiple biosensors for measuring electrocardiogram (ECG), photoplethysmographic signals (PPG), body temperature and physical activity. The main control module is the microcontroller, which collects, filters and transmits the data in real time. The data is processed locally, applying algorithms for extracting health parameters such as heart rate, heart rate variability (HRV) and abnormalities. PPG and ECG measurements are compared to validate the accuracy and reliability of the system. The obtained results show a high degree of correlation between the two methods, which confirms the applicability of PPG for continuous monitoring. The processing allows detection of potential health risks and automatic notification at critical values. The system is energy efficient and suitable for long-term use in wearable devices. The study shows the potential of cardio-based solutions for personalized healthcare and early diagnosis.

Keywords: *PPG; ECG; HRV; Cardio Sensor System; Signal Processing; Early Diagnosis.*

Introduction

Real-time monitoring of physiological parameters is a key element of modern healthcare, especially in the context of chronic diseases, cardiovascular risks and the need for remote medical care [1]. Traditional monitoring methods require a visit to a medical center and often do not provide continuous recording or immediate response to changes in the patient's condition. With the development of wearable technologies, new opportunities for intelligent, energy-efficient and affordable monitoring of vital signs are opening up [2]. Monitoring of signals such as electrocardiogram (ECG) and photoplethysmographic signals (PPG) allows for the assessment of cardiac activity, heart rate variability (HRV) and potential abnormalities such as arrhythmias [3]. Modern sensor systems combine these measurements with data on body temperature, physical activity and other indicators, creating a complete picture of the physiological state of the individual [4]. An important aspect of such systems is the combination of local processing (edge computing) for rapid response and cloud processing for complex analysis and predictive models through artificial intelligence [1], [5].

The study presents the development and testing of a compact, multi-sensor system designed for continuous monitoring of the health status of the body. The goal is to offer a solution that is portable, economical and at the same time reliable in the analysis of key biomedical signals. The emphasis is placed on the comparison between PPG and ECG measurements, the extraction of parameters such as HRV, and the possibilities for automatic notification of deviations [5]. The study demonstrates the applicability of such systems in the daily life of patients, athletes and in the context of telemedicine [6].

Overview

In recent years, health monitoring systems with a focus on cardiac monitoring have made significant progress. A key component of these systems are ECG and PPG sensors, widely used for continuous monitoring of cardiac functions and heart rate variability (HRV) (Allen, 2007 [2]; Esgalhado et al., 2022 [7]). Allen provides a fundamental analysis of PPG technologies, which, as a non-invasive method, allow for reliable real-time pulse data collection (Allen, 2007 [2]). Lu et al. (2009 [5]) contributes a comparative review suggesting that despite increased noise in PPG signals, HRV parameters extracted from PPG correlate well with those from ECG, supporting PPG's use as an affordable alternative for everyday IoT applications. Various systematic reviews address the architectures of IoT-based electrocardiographic frameworks, focusing on signal quality, data security, and the use of AI/ML at the edge (Huthart et al., 2020 [8]; Nardelli et al., 2020 [9]).

Ref. [10], [11] discuss the possibility of reconstructing an ECG signal from PPG data using hybrid models with CNN and Bi-LSTM, achieving excellent correlation (~0.98), suggesting future use in limited hardware resources.

Another important development is the study by Semchyshyn and Mykhalyk [12], who propose a portable IoT-based ECG monitoring solution utilizing the AD8232 sensor module and an Arduino Nano microcontroller. Data are transmitted securely and with low latency to the ThingSpeak cloud platform for real-time visualization and analysis. Remote Patient Monitoring (RPM) literature shows that IoT architectures incorporating both edge and cloud layers significantly enhance system reliability and responsiveness. This is especially vital for chronically ill patients and those in remote or underserved regions [13], [14].

Methods

The present study aims to develop and test a sensor system for continuous monitoring of basic physiological parameters, including heart rate, pulse, body temperature, and motor activity. The approach combines hardware prototyping, local data processing, and comparative analysis of measurements from PPG and ECG sensors (Fig. 1). This allows the system to function without dependence on internet connectivity and cloud services, making it suitable for remote areas, field conditions, and personal use [15].

The hardware architecture of the system includes several key components. An ECG sensor (MAX30003) [16] is used to record the electrical activity of the heart, while pulse waves and oxygen saturation are measured by a PPG module (MAX30102) [17]. The temperature sensor (MAX30205) [18] provides high-accuracy (±0.1°C) body temperature measurement. The LSM6DSL [19] integrated circuit, a combination of an accelerometer and a gyroscope, is used to detect motion, its change, and orientation. All these elements are connected to a Cortex-M33 microcontroller (STM32U5A5) [20], which performs local signal processing and can transmit data via Bluetooth(RN4871) [21] when needed. The components are mounted on a compact, wearable board.

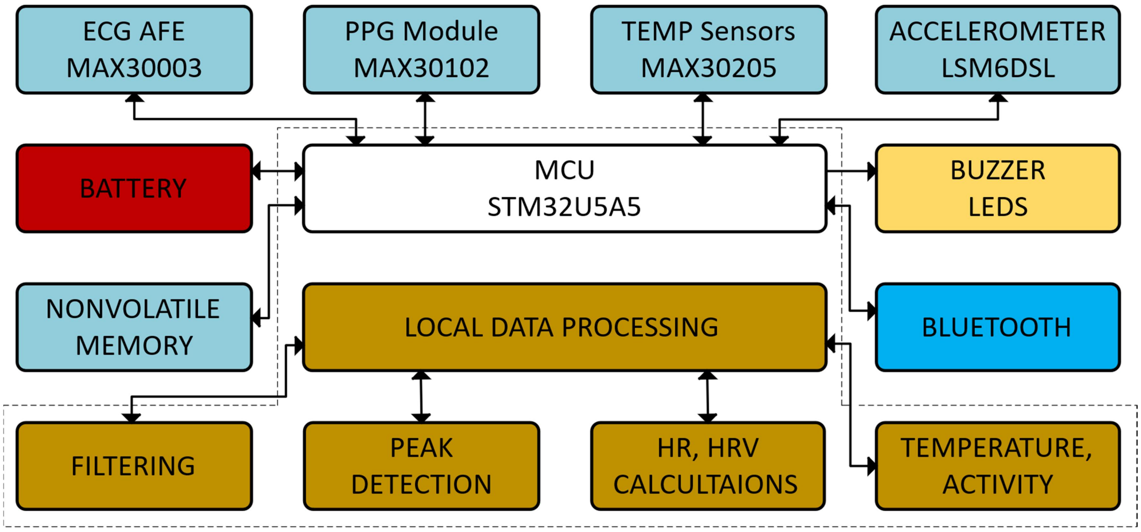

Fig. 1. Sensor monitoring system.

Fig. 2 shows the 3D model of the printed circuit board of the created prototype.

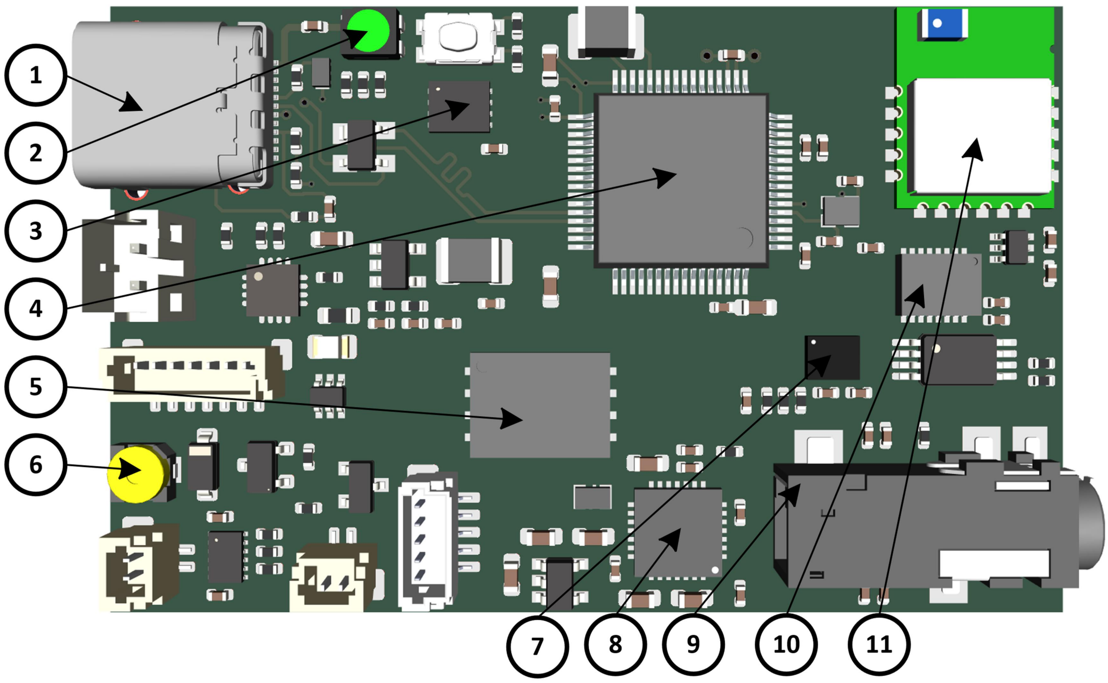

Fig. 2. 3D model of the printed circuit board.

The dimensions of the printed circuit board are 55x35mm. The main components are marked as follows:

1. USB connector used for charging the battery.
2. Signaling RGB LED.
3. Temperature sensor.
4. Microcontroller.
5. Memory for events that may occur.
6. Buzzer for signaling.
7. Accelerometer.
8. Analog frontend and ECG signal processing circuit.
9. Connector for connecting the electrodes for ECG lead.

10. Real-time clock.
11. Bluetooth connection module.

From a software point of view, the microcontroller is programmed in C/C++. The Nuttx real-time operating system [22] was used. Specialized libraries for sensor reading, digital filtration (Moving Average), as well as Bluetooth communication were created, taking into account the relatively limited resources of the microcontroller used. The system was experimentally tested on healthy volunteers aged between 30 and 55 years. Measurements were performed under controlled conditions both at rest and after a short physical activity. During each session, data were collected from several channels: ECG (3-electrode configuration), PPG (finger sensor), body temperature and accelerometric data along three axes.

Various biomedical indicators are extracted from the recorded signals. Heart rate (HR) is calculated from both ECG and PPG signals. By analyzing R-R intervals from ECG and interpeak intervals from PPG, standard heart rate variability (HRV) metrics – SDNN and RMSSD – are calculated. Data from the temperature sensor are used to estimate temperature trends, and the accelerometer provides information on motor activity and body orientation.

Signal preprocessing is essential to achieve reliable results. For this purpose, a Moving Average is applied to the PPG signals, as well as a low-pass Butterworth filter (5Hz) on the ECG. Peak detection is performed using an adaptive algorithm inspired by the classical Pan–Tompkins method for the QRS complex detection.

The HRV values extracted from PPG are compared with the corresponding values from ECG, which is considered the gold standard in clinical practice. This comparison allows to assess the reliability of the photoplethysmographic approach in analyzing cardiac activity in an IoT environment.

When testing the device on volunteers, measurements were taken at rest and after a short physical exertion. The PPG and ECG recordings were synchronized and saved to an SD card for subsequent analysis.

Key physiological parameters are extracted from each biosignal. Heart rate (HR) is determined from both the R–R intervals in the ECG signal and the pulse peaks in the PPG recording. Based on these intervals, key HRV metrics are calculated, including SDNN, RMSSD, and pNN50. Additionally, maximum and average body temperatures are analyzed, as well as physical activity levels extracted from accelerometer data.

A comparative analysis between PPG and ECG data is performed to assess accuracy – through correlation coefficient and mean absolute error. Due to the high sensitivity of PPG to movements, accelerometer data is used to eliminate artifacts during moments of activity. Regarding energy efficiency, the system is optimized for low consumption – below 80mA in active mode, which allows for autonomous operation for 10 to 12 hours with a lithium-ion battery with a capacity of 1000mAh.

Key indicators for HRV analysis are presented in Table 1, along with their normal values.

Table 1. Key indicators for analysis.

Parameter	Description	Normal values (approx.)	Meaning
HR	Heart rate	60–90 bpm	Out of range: tachycardia/bradycardia
SDNN	Total HRV (long-term)	> 100 ms = good, < 50 ms = low	ANS tonus indicator
SDANN	Variations between periods	> 70 ms = normal	Chronic low value = problem

Parameter	Description	Normal values (approx.)	Meaning
RMSSD	Parasympathetic activity (short-term)	> 30 ms (young); > 20 ms (adults)	Low value: stress, fatigue
pNN50	% of intervals with >50ms difference	> 15% = good	< 5%: high sympathetic load

RESULTS

The results presented in Table 2 show that the measured HRV parameters by PPG are comparable to those obtained by ECG, with no statistically significant differences (p > 0.05 for all metrics).

Table 2. Time domain parameters (PPG vs. ECG).

Parameter	PPG (N = 12) [Mean ± SD]	ECG (N = 12) [Mean ± SD]	p-Value PPG/ECG
SDNN (ms)	132.53 ± 24.09	128.15 ± 38.17	NS* (0.76)
SDANN (ms)	130.26 ± 32.23	126.48 ± 39.18	NS (0.79)
RMSSD (ms)	16.76 ± 4.08	14.92 ± 3.06	NS (0.18)
pNN50 (%)	8.55 ± 4.86	8.68 ± 3.38	NS (0.94)
SDNN Index (ms)	61.46 ± 24.12	63.13 ± 22.43	NS (0.87)

*NS — Not significant (p > 0.05)

The observed differences in mean values are within the acceptable physiological deviation, with SDNN and SDANN showing a high degree of agreement. RMSSD and pNN50, which are sensitive to short-term changes in the autonomic nervous system, also show good comparability between the two methods.

This confirms that PPG can be used as a reliable alternative to ECG for HRV monitoring in the context of IoT devices, especially in applications where non-invasiveness, energy efficiency and convenience are critical. However, it is important to note that additional filtering or corrections may be required in dynamic conditions (motion, load).

The developed algorithm for monitoring the health of the body uses locally collected data from ECG and PPG sensors to extract basic indicators of heart rate variability – HR, SDNN, RMSSD and pNN50. After detecting R-peaks in ECG or pulse peaks in PPG, the times between them (RR intervals) are calculated. From these intervals, the standard deviation (SDNN), root mean square deviation of consecutive differences (RMSSD) and the percentage of differences >50 ms (pNN50) are calculated.

The algorithm compares the calculated values with predefined thresholds based on clinical standards. For example, if SDNN is above 100 ms, RMSSD above 30 ms, and pNN50 above 15%, the condition is classified as normal. If SDNN is between 50 and 100 ms, and RMSSD between 20 and 30 ms, moderate strain or stress is assumed. Values below these thresholds (SDNN < 50 ms, RMSSD < 20 ms, pNN50 < 5%) are given a high-risk or abnormal warning.

Additionally, a difference check is performed between PPG and ECG. If the HRV values obtained from the two signals differ by more than 10%, the system considers signal noise or artifact and ignores the current value. The algorithm also includes motion detection via an accelerometer to account for distortions during activity.

Every minute, the health status is updated, which is displayed with a color code and with sound signals in case of critical indicators. For the different states normal, stress, risk there are different color and sound indications. Stress is considered when the HRV parameters are within the normal range, and risk when the values are outside the normal range (table 3).

Table 3. Monitoring parameters and thresholds.

Indicator	Normal state	Load (limit)	Risk (outside the norm)
SDNN (ms)	> 70 ms	50–70 ms	< 50 ms
RMSSD (ms)	> 40 ms	20–40 ms	< 20 ms
LF/HF Ratio	0.5–2.0	2.0–3.0	> 3.0 или < 0.5
HR (bpm)	60–90	90–110	> 110 или < 50
SampEn	> 1.2	0.8–1.2	< 0.8

When one or more parameters are at the limit, a load is reported. When at least one parameter is outside the norm, a risk state is reported. A block diagram of the proposed algorithm is presented in Fig. 3.

The system works autonomously, without the need for the Internet, and is adapted for wearable devices. Thus, the algorithm provides a fast, local and reliable assessment of cardiac regulation in real time.

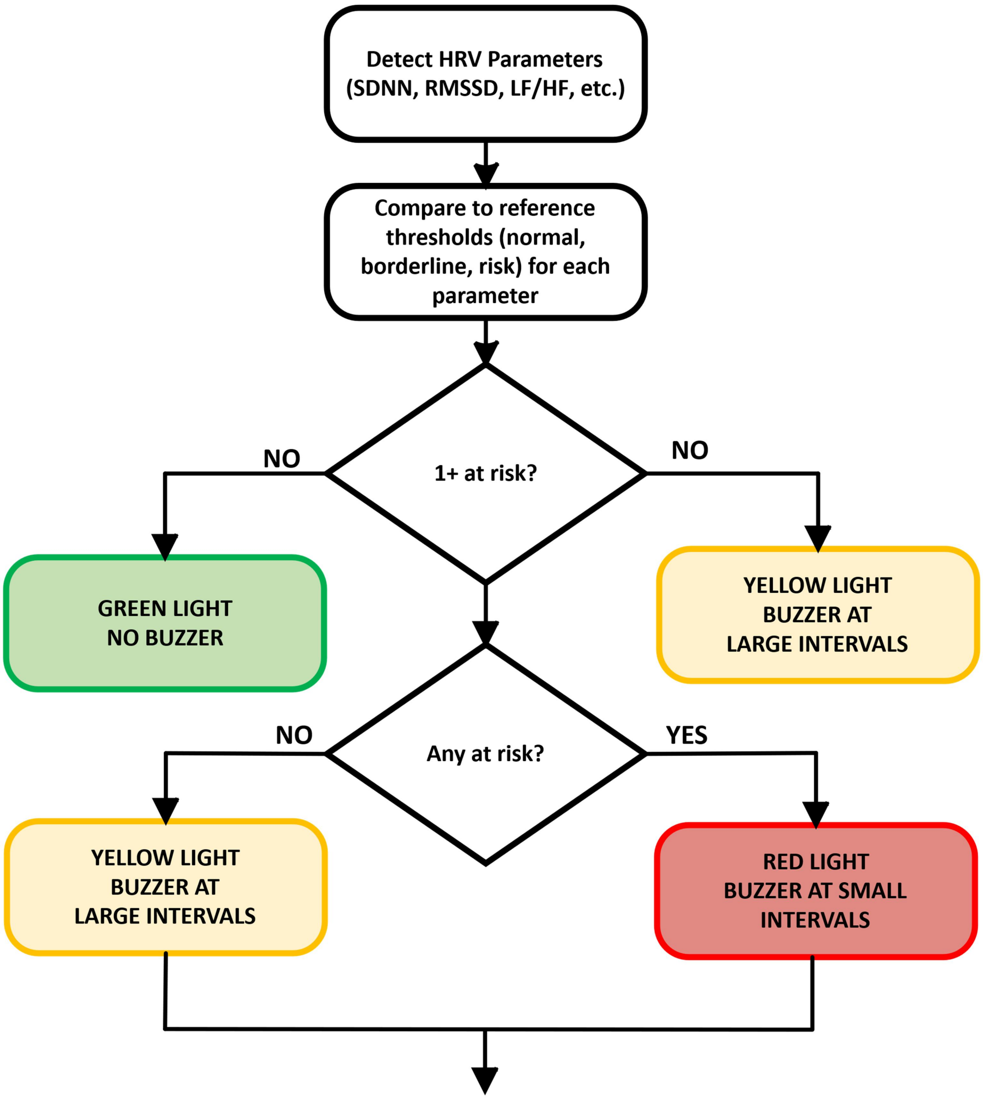

Fig 3. Decision-making algorithm.

DISCUSION

The proposed system for local cardiac monitoring demonstrates a high degree of reliability in extracting and analyzing HRV parameters from signals obtained by PPG and ECG sensors. The obtained values for SDNN, RMSSD and pNN50 confirm the comparability between the two types of sensors, especially after artifact correction and the use of local filtering algorithms. Although the statistical analysis did not reveal significant differences ($p > 0.05$), some deviation between the mean values is reported, which is within the physiological tolerance.

The system leverages the key advantages of local processing – low latency, independence from internet connectivity, and privacy. Unlike systems using a fully cloud-based architecture [1], [6], [15], which introduce latency and privacy risks, all processing is performed within the ARM Cortex-M33-based microcontroller (MCU).

The local approach makes it particularly suitable for home monitoring, in conditions of limited internet access, as well as for vulnerable groups – elderly or chronically ill patients. For comparison, in systems [4] and [12] local processing is also applied, but without a clear distinction between PPG and ECG signals, while in our system parallel processing and comparison between the two methods are implemented.

Systems like [10] and [11] use hybrid architecture or deep learning (Bi-LSTM, HADM), which provides higher accuracy but requires significant hardware resources or constant connection to the cloud. The present project aims to offer a functional alternative based on minimalism, energy efficiency and real field applicability.

As a limitation, PPG signals are susceptible to motion noise, as observed in other local systems [4], [8]. However, the inclusion of an accelerometer and artifact filtering logic minimizes this effect. The lack of cloud connectivity limits the possibilities for advanced analysis, but in return guarantees high autonomy and data protection. For future development, integration of lightweight machine learning models (e.g. TinyML) to run directly on the microcontroller, as done in [6] and [14], without sacrificing the local architecture, could be considered.

In conclusion, even without the use of a cloud platform, the proposed system provides an adequate and reliable assessment of cardiac regulation using a combination of PPG and ECG sensors. This makes it practical, economical and applicable in real conditions for early detection of physiological abnormalities.

CONCLUSION

This study presents the development and validation of an autonomous sensor system for cardiac monitoring that operates entirely locally, without the need for a cloud infrastructure. The combination of ECG and PPG sensors allows for simultaneous detection and comparison of vital signs, which increases the reliability of the analysis. The extracted HRV parameters (SDNN, RMSSD, pNN50, etc.) showed good consistency between the two types of signals, and additional statistical analysis confirmed the absence of significant differences at rest.

The developed classification algorithm, based on threshold logic and physiological limits, allows for real-time assessment of the health status, visualized through a color code on the display. The system is implemented on an energy-efficient platform (Cortex-M33) and is suitable for wearable devices and home use.

Among its main advantages are: autonomy, personal data protection, low cost, fast response to anomalies.

Limitations include PPG's sensitivity to motion and lack of deep learning, which could, however, be integrated in future versions via a lightweight ML model (e.g. TinyML) without breaking the local architecture.

In conclusion, the proposed system demonstrates that local processing in cardiac devices can be powerful and efficient enough to perform basic medical analysis. This makes it suitable for applications in telemedicine, monitoring, rehabilitation, and even early diagnosis in remote areas. Future developments should focus on adding mobile communication, patient-specific boundary customization, and expanding the sensor set.

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