Monitoring of Driver’s Biomedical Signals Using LoRa-based Wireless Communications

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Abstract This letter presents the design and implementation of a LoRa-based wireless communication system aimed at monitoring of driver’s biomedical signals in the car environments. The proposed system is composed of a sensor node, a LoRa gateway, and a cloud server. Each sensor node includes four parts as microcontroller unit, data collection unit, wireless communication unit, and supplied power unit. The microcontroller unit is mainly designed as the signal processing module to deal with the detection of abnormal ECG symptom such as left bundle branch block (LBBB), which is the most common symptoms of myocardial infarction. The data collection unit contains a sequential stage of the instrumentation amplifier and the filter blocks. The notification of LBBB detection is then transmitted to the LoRa gateway by wireless communication unit. The LoRa gateway with multiple wireless interfaces is designed to collect the information from the sensor node to transmit to cloud server. The experimental results are conducted to evaluate the detection performance of LBBB by means of MIT-BIH arrhythmia database.

Keywords: left bundle branch block; LoRa; ECG

1. Introduction

As the population of the developed countries presents an aging trend, the age of drivers in the future will also gradually become aging, resulting in physical and mental suddenness of drivers. According to recent literatures [1], up to 30% of car crashes occurred in the presence of sleepy driving or driver’s abnormal vital signals, which might come from the cardiovascular disease (CVD) cause. Among CVD symptoms, cardiac arrhythmia is the most common symptoms for myocardial infarction and it is usually a cardiac conduction abnormality seen on the electrocardiogram (ECG). ECG can record the process of cardiac excitability, transmission, and repolarization, such as LBBB, mainly depend on the ECG signal and resembles a critical functionality performed by the heart [2]. The combinations of Q wave, R wave and S wave make a QRS complex which contains the maximum information of the ECG. In medical area, P, QRS and T waves represent atrial depolarization, ventricular depolarization and ventricular repolarization, respectively, which play an important role in detection of cardiac arrhythmia [3]. There have been large amounts of work on developing for left bundle branch block (LBBB) detection [4]-[24], where the detection of LBBB will be discussed in section 2. On the other hand, rapid progression in wireless communication technologies has prompted continuous studies on the emergence of internet of thing (IoT), which makes it possible that the users can obtain the real-time vital signals at any places and anytime. Inspired by the reasons mentioned above, a novel real-time IoT system aimed at monitoring of driver’s biomedical signals is proposed in this letter. The proposed system is composed of a sensor node, a LoRa gateway, and a cloud server. Each sensor node includes electrocardiogram (ECG) sensor module, signal processing module, and LoRa module. The ECG sensor module contains a sequential stage of instrumentation amplifier and filter blocks, the signal processing module provides a real-time algorithm for the detection of abnormal LBBB symptom, which is the most common symptoms of myocardial infarction, and the notification of LBBB detection are then transmitted to the LoRa gateway by LoRa module. The LoRa gateway with multiple wireless interfaces is designed to collect the information from the sensor node to transmit to cloud server.

2. The related works to LBBB detection

Traditionally, the diagnosis of cardiovascular diseases, such as LBBB, mainly depend on the ECG. ECG can record the process of cardiac excitability, transmission, and recovery. In order to analyze the ECG signals, two steps should be performed, i.e., feature extraction and pattern
classification. In general, there are two main groups of ECG feature extraction algorithms, which are wave delineation algorithms and QRS detection algorithms [4]. For wave delineation algorithms, they determine the peaks and boundaries of the individual QRS complexes, P and T waves. Among popular methods, the phasor transforms [5], moving average filters [6] and morphological mathematical filtering with Elgendi’s algorithm [7] have been applied to detect ECG fiducial points. In addition, due to the high amplitude of the QRS complex, it is the most characteristic waveform of the ECG signal and can be detected easier than the other waves. Wavelet transform [8], phase-space reconstruction [9], adaptive thresholding [10] have been proposed within the last four decades, which are categorized as QRS detection algorithms.

In the classification step, the extracted features are fed into some types of classifiers. Recently, there are a lot of ECG classification algorithms having been proposed, such as convolutional neural network (CNN) [11], support vector machines (SVM) [12], cluster analysis (CA) [13], random forests (RF) [14], optimum-path forest (OPF) [15], decision tree [16], logistic regression [17], neuro-fuzzy system [18], K-nearest neighbors (KNN) classification method [19], etc. After performing the two steps for the analysis of ECG signals, the recognition of LBBB, which is one of the predominant ECG heartbeats from MIT-BIH arrhythmia database, can be accomplished. Recently, hardware implementation systems for the ECG analysis systems are published in [20]-[26].

3. System design and implementation

Fig. 1 shows the scenario of the proposed overall system which mainly contains many sensor nodes from vehicles, one LoRa gateway in a sector, and one cloud server. Each sensor node collects ECG analog signals from the driver by a sequential stage of the instrumentation amplifier and the filter blocks and then transformed into the digital signals through analog-to-digital converter (ADC). After some signal processing process such as digital filtering and LBBB detection, the resultant filtered raw data of ECG signals and LBBB detection can be obtained to fed into the input of LoRa module. The function of LoRa gateway is to receive the information sent by sensor nodes and then transmit to cloud server by wifi signals. The function of cloud server is to receive the data and store them in the pre-defined database, where the users could access or browse via website protocol such as HTTP. In the following subsections, we will demonstrate the hardware and software designs of each component in detailed.

3.1 Hardware Implementation of sensor node

The purpose of a sensor node is to collect the ECG raw data and then detect the abnormal ECG symptom. When an abnormal ECG symptom is detected, the notification of real-time is achieved by means of LoRa transmission.

The hardware design block diagram is shown in Fig.2, where it contains four parts such as microcontroller unit, data collection unit, wireless communication unit, and supplied power unit. In microcontroller unit, we use the low power 8-bit RISC-based microcontroller with part number of ATMEGA 328. The ATMEGA 328 has 1024-byte EEPROM, 2K byte SRAM, 23 general purpose I/O lines, three flexible timers with compare modes, internal and external interrupts, serial programmable UART, a byte-oriented 2-wire serial interface, serial peripheral interface (SPI) serial port, and a 6-channel 10-bit analog-to-digital converter (ADC) whose conversion time is 10 us. The maximum microcontroller speed is 20 MIPS.

The hardware design of data collection unit consists of a sequential stage of instrumentation amplifier, low pass filter, band-reject filter and post amplifier, where the detailed circuit design is provided in Fig.3. Firstly, the ECG electrodes are connected to the instrumentation amplifier manufactured by Texas Instruments company has high input impedance, high common mode rejection ratio, and low zero drift. It also provides a fixed amplification for the ECG signal. With its CMRR specification of 94 dB extended up to 3 kHz, the INA321 rejects the common-mode noise signals including the line frequency and its harmonics. Secondly, a low pass filter with a cut-off frequency of 100 Hz is used after to remove the high-frequency noise of ECG raw signals. As seen in Fig.4, the low-pass filter provide a 6dB gain for ECG raw signals below 100 Hz and the band-reject filter provide a -7dB gain degradation for ECG raw signals with 100 Hz.
Figure 2. The block diagram of sensor node.

Figure 3. The hardware design of data collection unit in sensor node.

Figure 4. The simulation results of frequency response (a) low-pass filter; (b) band-reject filter.

Figure 5. LoRa module.

Noted that all circuits within data collection unit are powered by 5 V dc. Finally, the filtered signal is amplified by a post amplifier with a 20dB gain and then the amplified signals are fed into microcontroller unit to detect abnormal ECG symptom. The detailed signal processing algorithm for detection of abnormal ECG symptom is illustrated in the following section. The hardware design of wireless communication unit is designed as the Dragino LoRa Shield module, which is a long range transceiver on a Arduino shield form factor and based on open source library. The physical diagram of adopted LoRa module is shown in Fig.5. This module is connected with the microcontroller unit by SPI. To avoid lengthy descriptions, only the parameters regarding to wireless transmission are given as follows. The used frequency band, bit rate, and dc voltage is 433MHz, 300 kbps, and 5 V dc, respectively. The other parameters can be refereed in [27]-[28]. In power unit, a voltage regulator is employed to transform 12 V dc from the vehicle to 5V dc.

3.2 Hardware Implementation of LoRa gateway

The purpose of a LoRa gateway is to communicate with multiple sensor nodes at the same time. Except for data collection unit, it is composed of microcontroller unit, wireless communication unit, and supplied power unit similar to that of sensor nodes. The block diagram of a LoRa gateway is shown in Fig.6. In LoRa gateway, we use the same microcontroller with part number of ATMEGA 328 and LoRa module as sensor nodes. In wireless communication unit, Wifi module with the part number of ESP8266 is used to send the notification of abnormal ECG symptom to the cloud server. The only
difference is that the power source of a LoRa gateway is the AC source of 120V. It is necessary to transform the AC power source to DC source of 12V and then obtain the DC source of 5V by voltage regulator. All modules within a LoRa gateway are powered by 5 V dc.

3.3 LBBB detection algorithm
In this subsection, we will introduce the LBBB detection algorithm in details. According to MIT-BIH arrhythmia database, only recordings 109, 111, 207, and 214 have LBBB symptom, where the corresponding waveforms are provided in Fig.7 (a)-(d). Obviously, two phenomenon can be observed in Fig.7 (a) and (d). First, the time durations of QRS complex signal in Fig.7 (a) and (d) are larger than 120 ms. Secondly, no T waves exist in Fig.7 (a) and (d). For Fig.7 (b), there is a second maximum peak followed by maximum peak of R wave. For Fig.7 (c), there is a maximum negative peak followed by the maximum peak of R wave. On the basis of mentioned above, we could create the time-domain LBBB detection schemes based on detection of R wave. Generally, Pan-Tompkins (P&T) [8] and So-Chen (S&C) [9] methods are two well-known R wave detection. The detailed steps of the proposed LBBB detection are given as follows.

**Step 1:** Using P&T or S&C to detect the R peak of ECG raw data.

**Step 2:** Based on the positions of the determined R peak, a 512-point synthesis signal is obtained by taking data points of R peak form the backward 255th point to the forward 256th point.

**Step 3:** Estimate the time duration of QRS complex signal $T_{QRS}$, if $T_{QRS} \geq 120$ ms and no T waves can be estimated, the positions of the determined R peak in step 2 is determined to be the LBBB symptom.

**Step 4:** If $T_{QRS} < 120$ ms and a maximum negative R peak can be estimated, the positions of the maximum negative R peak is also determined to be the LBBB symptom. Moreover, if there is a second maximum peak on the left of the determined R peak in the step 1, the positions of the determined R peak is presented as the LBBB.

4. Experimental results
The experimental setup of the sensor node is shown in Fig.8. In order to evaluate the proposed LBBB detection in real-time practical environment, we store the original ECG raw data of records 109, 111, 207, and 214, which comes from the MIT-BIH arrhythmia database, in the pattern generator [29]-[30]. The goal of the pattern generator is to generate the specific ECG pattern, which consists of a STM32 evaluation board and a non-inverting amplifier of maximum gain of 2dB. The sensor node is composed of ATMega 328 evaluation board and
LoRa module. Noted that MIT-BIH database consists of annotated records of subjects suffering from various arrhythmias digitized at 360 Hz with 11-bit resolution over a 10 mV range. The stored ECG raw data are then inputted to the sensor node by ADC with sampling rate of at least 400 Hz. Afterward, the sensor node performs the LBBB detection algorithm to validate the LBBB detection accuracy. The experimental results of the LBBB detection are shown in Table I. The total number of LBBB beats for records 109, 111, 207, and 214 are 2492, 2123, 1457, and 2003, respectively. As can be seen in Table I, the detection accuracies of the LBBB with different R peak detection schemes are more than 91%. The average detection accuracy of the LBBB with S&C algorithm is better than that of P&T algorithm because the relating R peak detection is more accurate.

Table 1 LBBB detection accuracy.

| R peak detection | P&T     | S&C     |
|------------------|---------|---------|
| records 109      | 92.14%  | 94.15%  |
| records 111      | 93.21%  | 95.21%  |
| records 207      | 91.08%  | 93.43%  |
| records 214      | 93.36%  | 95.43%  |
| Average          | 92.45%  | 94.56%  |

6. Conclusion

In this letter, a real-time LBBB detection algorithm was achieved by the proposed scheme, which contains a sensor node, a LoRa gateway, and a cloud server. It is observed from the experimental results that the detection accuracies of the LBBB with different R peak detection schemes are more than 91%, which provides the potential solutions for monitoring the driver’s biomedical signals.

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