# Wireless Body-Area Network Time Synchronization using R Peak Reference Broadcasts

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***Abstract*—Telemonitoring of biosignals is a growing area of research due to the aging world population. Telemonitoring utilizes a wireless body-area network (WBAN) consisting of wearable biosignal sensors equipped with ultra low power radios. The measured data from each sensor on the patient is sent to a smartphone, which then sends the data to a healthcare provider via the internet. To enable real-time telemonitoring of the biosignals, it is desirable to have accurate timestamped data from the sensors in the WBAN. This is especially important for data consistency to sensors that store their measured data and infrequently send it to the smartphone. This letter presents a novel synchronization algorithm that exploits the R peaks of the electrocardiogram (ECG) data that is transmitted to the smartphone. To the best of the author's knowledge, this is the first time the R peak has been used as a signal of opportunity (i.e., any signal that is used for positioning, navigation, or timing (PNT), even though the signal is not originally intended for PNT applications) for synchronization. The R peaks serve as the reference broadcast for the WBAN in a reference-broadcast synchronization (RBS) scheme. Simulation results using low cost sensors and an actual 24 hour ECG recording show that the smartphone can determine the timing of the WBAN sensor data accurately at any time within the 24 hour period to within ~30µs. Without synchronization, the sensor data would have a timing offset of 8 seconds by the end of the 24 hours.**

***Index Terms*—body sensor networks, clocks, synchronization, timing**

## I. Introduction

Telemonitoring of biosignals is a growing area of research due to the aging world population. Telemonitoring utilizes a wireless body-area network (WBAN) consisting of wearable biosignal sensors equipped with ultra low power radios. The measured data from each sensor on the patient is sent to a smartphone, which then sends the data to a healthcare provider via the internet. Thus, the patient's health is monitored continuously and remotely in real-time without the need for the patient to visit their doctor. [1]

To enable real-time telemonitoring of the biosignals, it is desirable to have accurate timestamped data from the sensors in the WBAN. For example, if a sensor uses a low cost 32,768 Hz crystal oscillator with a frequency stability of 100 ppm, the time offset can be as high as 259 seconds after 1 month of use without any synchronization algorithm. Accurate timestamped data is especially important for data consistency to sensors that store their measured data and infrequently send it to the smartphone [2]-[3].

One of the major constraints in WBANs is power consumption, since these sensors are meant to be used for weeks, months, and even years. The power consumed by wirelessly transmitting the data to the smartphone is orders of magnitude higher than the power consumed by any other operation (e.g., analog-to-digital conversion and digital signal processing), and thus, must be minimized [4].

The contribution of this letter is a novel synchronization algorithm applicable to WBANs. All of the sensors in the WBAN exploit the R peaks of the existing electrocardiogram (ECG) data that the ECG sensor transmits to the smartphone, so no additional power is consumed by transmitting special timing messages. To the best of the author's knowledge, this is the first time the R peak has been used as a signal of opportunity (i.e., any signal that is used for positioning, navigation, or timing (PNT), even though the signal is not originally intended for PNT applications) for synchronization. The R peaks serve as the reference broadcast for the WBAN in a reference-broadcast synchronization (RBS) scheme. The layout of the paper is as follows. Section II reviews network synchronization, RBS, and the proposed synchronization algorithm. Section III discusses the clock model and receiver characteristics used in the subsequent simulation results of the proposed algorithm's performance in a WBAN. The paper is concluded in Section IV.

## II. Network Synchronization

The difficulty faced in network synchronization is due to non-deterministic latencies involved in the exchange of timing messages between nodes. The four sources of latency in sending a timing message from one node to another are [5]:

1) Send time – the time taken to create the message and transfer it to the network interface
2) Access time – the time spent waiting for the network

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interface to gain access to the transmission channel

3) Propagation time – the time taken for the message to be physically transferred from the sending node to receiving node
4) Receive time – the time taken by the receiver's network interface to receive and process the message

The propagation time is small for WBANs (i.e., on the order of nanoseconds since all of the sensors are located on various parts of the body), so the send time, access time, and receive time are the main sources of non-deterministic latencies. Furthermore, the latencies due to the send time and access time are larger than the latency due to receive time [6].

### *A. Reference-Broadcast Synchronization [7]*

A popular network synchronization algorithm that eliminates the non-deterministic latencies due to send time and access time is RBS. This is accomplished by using a broadcast message as a reference to synchronize a set of receivers with each other. Each node in the set receives the same broadcast message, so the only non-deterministic latencies experienced by each node are due to their respective propagation times and receive times.

RBS works as follows: for simplicity, assume the set of receivers consists of two nodes $i$ and $j$. Let $t_{i,A}$ denote the time that event $A$ occurs with respect to node $i$'s clock. A transmitting node broadcasts message $B$ to nodes $i$ and $j$. $i$ and $j$ record the time that message $B$ is received, which results in timestamps $t_{i,B}$ and $t_{j,B}$, respectively. This step is repeated for $N$ distinct broadcast messages, which results in $\mathbf{t}_i = [t_{i,B1} \ldots t_{i,BN}]^T$ and $\mathbf{t}_j = [t_{j,B1} \ldots t_{j,BN}]^T$. Then, nodes $i$ and $j$ exchange their $N$ timestamps. From the perspective of node $i$, it performs least squares (LS) regression to find the best linear fit to $\mathbf{y} = m\mathbf{x}+b$ where $\mathbf{y} = \mathbf{t}_j - \mathbf{t}_i$ and $\mathbf{x} = \mathbf{t}_i$. $m$ is the clock skew (i.e., the rate of change of the difference in time between two clocks) as measured by $i$, and $b$ is the difference in time between the two clocks at time $t_{i,B1}$. This enables node $i$ to convert any timestamps from node $j$'s clock to the timestamp that would have been generated by node $i$'s clock. Node $j$ can do a similar process, hence the set of receivers are synchronized with each other.

The advantages of RBS are 1) more precise synchronization can be achieved when compared to conventional synchronization algorithms that measure the round-trip delay since the non-deterministic latencies due to send time and access time are eliminated, and 2) post-facto synchronization is possible (i.e., previous time offsets can be estimated at a later time).

### *B. Adaptation of RBS to WBANs*

The WBAN is assumed to be a single-hop network (i.e., every device can directly communicate with any other device) consisting of an ECG sensor, smartphone, and other wearable sensors (e.g., smartwatch, inertial measurement units, temperature sensors, galvanic skin response sensors, etc.). Since ECG data is typically analyzed for RR interval and heart-rate-variability, two different system architectures are proposed [3], [8]-[9]:

1) The ECG sensor transmits a short flag message every time an R peak is detected. This flag serves as the broadcast message to all devices in the WBAN besides the ECG sensor. Each receiving device records the time that it receives the message.
2) The ECG sensor transmits the entire ECG data stream, either compressed or uncompressed. The data stream serves as the broadcast message to all devices in the WBAN besides the ECG sensor. Each receiving device $i$ performs R peak detection on the data stream and determines the time that each R peak occurred. The R peak serves as a good timestamp point due to its unique shape and ease of identification [10]. The set of times that each peak occurs results in $\mathbf{t}_i$.

Note that in both architectures, the ECG message is intended for the smartphone, but can be received by every device in the WBAN. The broadcast message is assumed to be compliant with short-range, low power wireless communication standards (e.g., IEEE 802.15.6 or Bluetooth), so that every device besides the ECG sensor can receive and process the message without any additional hardware. When compared to the second architecture, the first architecture does not require R peak detection at the receiving devices, consumes less power (since the ECG sensor transmits significantly less data), and has smaller receive time latencies, so it is the architecture adopted for the rest of this letter.

Whenever any of the wearable sensors $j$ needs to transfer its data to the smartphone, it also sends $N$ timestamps (corresponding to the reception times of the broadcast messages) so that the smartphone can convert the timestamps from $j$'s clock to the timestamps that would have been generated by the smartphone's clock. Note that in cases where the sensors store their data and infrequently send it to the smartphone, the $N$ timestamps correspond to the time window where the data of interest was measured. It is assumed that the smartphone is synchronized to within 1.5μs of Coordinated Universal Time (UTC) [11], so that its clock does not deviate much from true time unlike the sensor clock.

Unlike the previous section where LS regression is used to find the best linear fit, the author proposes to use Deming regression which accounts for errors in the timestamps (due to the clock offset relative to UTC and non-deterministic receive time latencies) of both the sensor and smartphone. Note that this is the first time (to the best of the author's knowledge) that RBS is used with Deming regression (as opposed to LS or weighted LS). Fig. 1 shows the difference between the two types of regression: LS regression only accounts for errors in the y-axis data (left plot) whereas Deming regression accounts for errors in both the x- and y-axis data (right plot). Note that the errors in the x-axis data are increased by $10^{11}$ for ease of visibility.

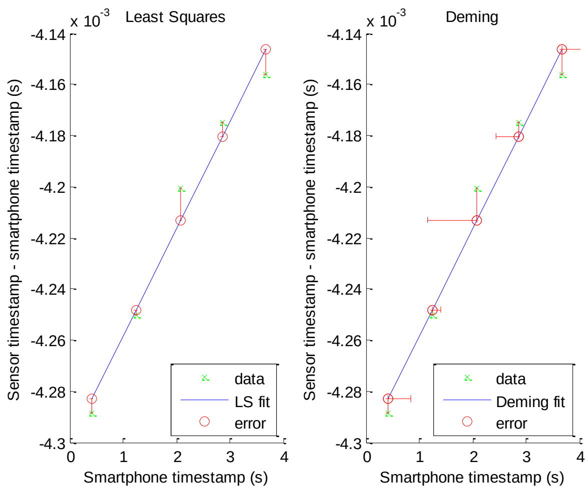


Fig. 1. Least squares regression vs. Deming regression

## III. Simulation Results

In this section, simulation results are provided to evaluate the synchronization performance of the proposed RBS algorithm in a WBAN. First, the clock model used to generate time and frequency data is presented. Then, the receive time latency model is discussed. Finally, the synchronization performance of the proposed RBS algorithm is presented.

### A. Clock Model

The clock offset $\theta_n(k)$ is the difference in time between clock $n$'s time and true time at discrete time $k$. The commonly used two state clock model given by (1) can be used to effectively model clock dynamics [12].

$$\begin{bmatrix} \theta_n(k) \\ \xi_n(k) \end{bmatrix} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \theta_n(k-1) \\ \xi_n(k-1) \end{bmatrix} + \vec{w}_n(k) \qquad (1)$$

$T$ is the time interval between state updates, $\xi_n$ is a Wiener process contributing to the rate of change of $\theta_n$, and $\vec{w}_n(k)$ is a zero mean process noise with covariance

$$Q_n = \begin{bmatrix} q_{1,n}T + q_{2,n}T^3/3 & q_{2,n}T^2/2 \\ q_{2,n}T^2/2 & q_{2,n}T \end{bmatrix} \qquad (2)$$

$q_{1,n}$ and $q_{2,n}$ can be obtained from the Allan variance of sensor node $n$'s oscillator, which is given by

$$\sigma_n^2(\tau) = \frac{q_{1,n}}{\tau} + \frac{q_{2,n}\tau}{3} \qquad (3)$$

### B. Receive Time Latency

In [7], RBS was implemented and tested on a network of Berkeley Motes. The Berkeley Mote is a small, low power, low cost, radio and sensor platform [13]. In [7], the receive time latency was experimentally shown to be Gaussian with zero mean and standard deviation 11.1μs. Also, the resolution of the receive timestamp of the reference broadcast messages was stated to be 2μs. Hence, the performance of the proposed RBS algorithm is simulated using these receiver characteristics of the Berkeley Mote platform.

### C. Synchronization Performance

The simulated WBAN consists of an ECG sensor, smartphone, and a Berkeley Mote. Record 16773 of the MIT-BIH Normal Sinus Rhythm Database is used as the ECG data which consists of a 24 hour ECG recording of a 26 year old male with no significant arrhythmia [14]. The locations of the R peaks are determined using MATLAB's findpeaks function. A total of 81,983 R peaks occurred in the 24 hour period.

Both the smartphone and Berkeley Mote use the receiver characteristics from the previous section. The smartphone is synchronized to within 1.5μs of UTC (i.e., its time offset is Gaussian with zero mean and standard deviation 1.5μs). The Berkeley Mote uses a 32,768 Hz crystal oscillator with a frequency stability of 100 ppm, and the parameters $q_{1,n}$ and $q_{2,n}$ are determined using the Allan variance given for a poor crystal oscillator in [15]. Without any synchronization, the clock offset of the Berkeley Mote is over 8s by the end of the 24 hour period.

Fig. 2 shows the synchronization performance of the proposed RBS algorithm. Fig. 2 depicts the estimation error of the Deming regression line using a window of $N$ timestamps (similar to Fig. 1.b.). More specifically, the estimation error is given by the 2-norm of the difference between the true data point (formed using the true timestamps without any errors) and estimated data point (using Deming regression with the measured timestamps). The estimation error is calculated for each of the 81,983 data points, and each circle in Fig. 2 is the value that 95.45% of the estimation errors are less than for a

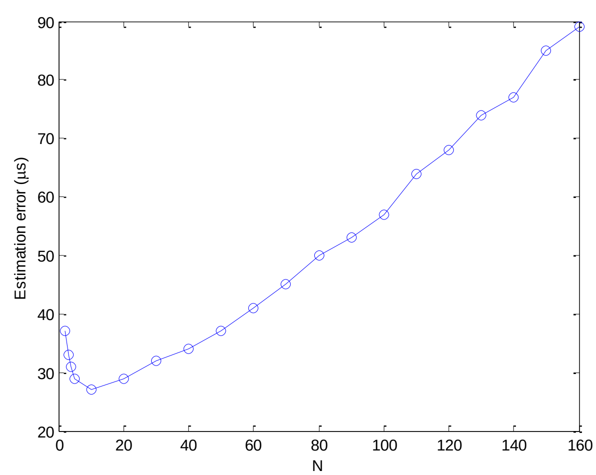


Fig. 2. Synchronization performance of proposed RBS algorithm vs. $N$

given $N$. For example, 95.45% of the 81,983 estimation errors are less than 27μs using a window size of $N = 10$ timestamps. The best synchronization accuracy is achieved for approximately $2 \leq N \leq 50$, which is a short enough window of time where the linear relationship between the clocks of the sensor and smartphone holds [16]. For $N > 50$, the linear approximation degrades along with the synchronization performance.

Fig. 3 compares the synchronization performance of the proposed RBS algorithm using LS regression in place of Deming regression. The estimation error for each of the 81,983 data points obtained using LS regression is subtracted from the estimation error obtained using Deming regression, and taking the mean, yields Fig. 3. Fig. 3 shows that Deming regression performs slightly better than LS regression because the curve is negative. Note that in the range of $10 \leq N \leq 50$ (where the best synchronization accuracy is achieved from Fig. 2), Deming regression performs over ten nanoseconds better on average than LS regression. Of course, this improvement is negligible since the error budget is on the order of tens of microseconds, but it can become important if precise hardware timestamps are available.

## IV. Conclusion

In this letter, a novel synchronization algorithm was presented to enable real-time telemonitoring of the biosignals in WBANs by using R peaks as the reference broadcast in a RBS scheme. In terms of power consumption, the algorithm leverages the existing ECG data that is transmitted from the ECG sensor, so no additional power is consumed in transmitting the reference broadcast. The only additional power is consumed in transmitting a few timestamps of when the broadcast is received, which only occurs when the sensor needs to send its data to the smartphone. Furthermore, unnecessary energy is not wasted (as with conventional synchronization algorithms that synchronize the clocks continuously) because post facto synchronization allows the smartphone to convert the timestamps of the sensor's clock to the timestamps that would have been generated by the smartphone's clock at a later time. This is critical for data consistency to sensors that store their measured data and infrequently send it to the smartphone (e.g., nightly readouts).

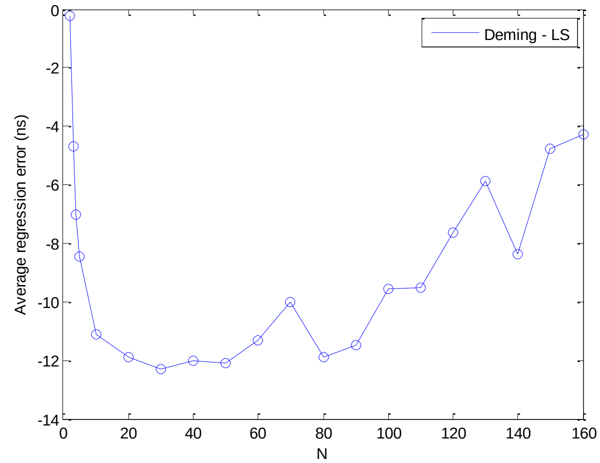


Fig. 3. Synchronization performance of proposed RBS algorithm minus synchronization performance using LS regression in place of Deming regression

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