Improving Wearable Sensor Data Quality Using Context Markers

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ABSTRACT

A major challenge in human activity recognition over long periods with multiple sensors is clock synchronization of independent data streams. Poor clock synchronization can lead to poor data and classifiers. In this paper, we propose a hybrid synchronization approach that combines NTP (Network Time Protocol) and context markers. Our evaluation shows that our approach significantly reduces synchronization error (20 ms) when compared to approaches that rely solely on NTP or sensor events. Our proposed approach can be applied to any wearable sensor where an independent sensor stream requires synchronization.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**.

KEYWORDS

Clock synchronization, clock drifts, wearable sensors

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1 INTRODUCTION

Multiple wearable and ubiquitous sensors are often used to collect and interpret participants' behavior, activities, as well as sense the surrounding context. One of the main challenges for multiple sensor systems is *clock synchronization* [1, 6]. Precise clock synchronization is important during training and deployment[12]. Furthermore, as the internal clocks do not run at the same rate, accumulated clock drift over time can cause synchronization misalignment across multiple sensors leading to reduced modeling capabilities [4, 6].

In this paper, we demonstrate an approach to synchronize clocks among multiple wearable devices to enable more accurate data collection. Our approach uses a combination of NTP (Network Time Protocol) and context markers. We define context markers to be identifiable physical actions that are known to have been simultaneously detected by multiple sensors. We then evaluate the performance of each method separately and in combination on multiple Myo armbands[1]. Our results show that our hybrid approach reduces the accumulating error to around 20 ms over 15 hours, outperforming the performance of standalone NTP (250 ms) and standalone context markers (1312 ms). Our method is applicable to other types of wearable devices and for scenarios where data synchronization is required.

2 RELATED WORK

Clock synchronization is a well-known problem within the UbiComp community[6, 10]. One of the widely adopted synchronization methods is based on message passing and time distribution protocols, including the Network Time Protocol (NTP) [7] and Precision Time Protocol (PTP) [2]). In their work, Sundararaman et al. [12] state that these network-based clock synchronization technologies exchange specific messages to align clocks of distributed sensors. However, these protocols increase the overhead of sensor network communications and sensors' energy consumption.

[1]https://support.getmyo.com/hc/en-us

Whereas many devices (e.g., laptops, smartphones) have internal clocks and do not need receivers to assign an absolute timestamp, a wide range of wearable equipment (e.g., Myo armband, Empatica E4 [2] wristband) requires a receiver to assign such a timestamp during data collection. For these cases, Bannach et al. [1] propose an event-based approach to synchronize data streams by periodically performing predefined synchronization context markers (e.g., 'clap', 'push-release' and 'shake'), which can be automatically detected and used for clock synchronization across multiple wearable sensors. The authors suggest using well-defined automated synchronization context markers to identify stream synchronizations (e.g., accelerometer, sound, force, motion tracking), and achieve a synchronization error of 300 ms for more than 80% of the stream.

However, this synchronizing approach requires participants to perform predefined synchronization context markers throughout the experiments, which may result in interruptions. Unlike Bannach et al. [1], in our work we limit our event to one sequence of context markers – hitting the table with the fist several times in sequence – which we perform at the beginning of the experiment (not periodically throughout the experiment). We use these context markers to create a sequence of pulses for detecting synchronization points before the Myo armbands are placed on the user. This helps us eliminate missing inserted events as well as temporal jitter [1].

3 PROPOSED APPROACH

Our proposed clock synchronization approach consists of three steps. In the first step, we use NTP to record the receivers' time drift over a 15-hour time period. This step is performed only once throughout the whole experiment and requires Internet access, while Step 2 and 3 are performed offline. In the second step, we generate a sequence of context markers ('hitting on the table with the fist') before starting the data collection procedure. In the last step, we use the context marker (Step 2) to align clocks across multiple sensors, and the NTP records (Step 1) to maintain the clock synchronization over long periods.

Network Time Protocol (NTP)

Prior research demonstrates that an NTP service is able to provide time offsets between clients and Coordinated Universal Time (UTC) [8]. However, network congestion and asymmetric routes may cause errors in excess of 100 ms [8]. In addition, time drift between wearable sensors and their receivers is another issue that cannot be overlooked, as it drifts for more than 1000 ms per day and leads to accumulation of errors [12]. Based on these constraints, we use the ntplib[3] Python library to record the changes of time offset from each Myo armband receiver (as each of the receivers has different clock drifts) and the NTP service is called every 10,000 ms over a 15-hour time period, while clock synchronization services from receivers are turned off. From Figure 1, we observe that interpreted clock drift rate from one Myo armband receiver is linear, which is in line with prior research [9].

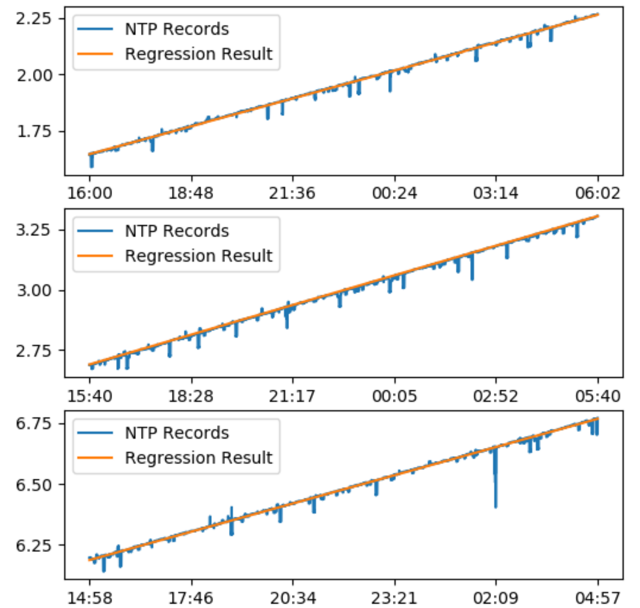

Figure 1: 15-hour NTP records from one Myo armband receiver observed in three different days

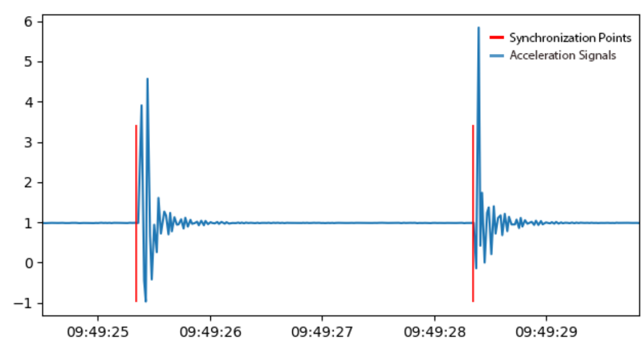

Figure 2: Signal pattern of 'hitting the table with the fist' context marker from accelerometer (X-axis)

Detecting Synchronization Context Markers

It is common to use context markers to align clocks between multiple sensors. For example, Bannach et al. [1] proposed

[2] https://www.empatica.com/en-int/research/e4/

[3] https://pypi.org/project/ntplib/

three predefined synchronization context markers, including 'clap', 'push-release' of a button and 'shake'. Based on 'clap' and 'push-release' context markers, whose signal patterns have a stable silence and are followed by a fast pulse, we adopt a new context marker of 'hitting the table with the fist' and show its signal pattern in Figure 2. To perform a 'hitting' context marker, we place all armbands close to each other on a table (to ensure that the starting point of the context marker is the same for all the devices), and hit the table with the fist to create short pulses. We used 'hitting the table with the fist' context markers for aligning clocks between multiple Myo armbands, because it is easily detected by accelerometers of the devices. The synchronization point is determined as the start point of the signal.

Combining NTP and Context Markers

After collecting a sequence of 'hitting the table with the fist' context markers, we first try to match these synchronization points across the individual data streams. As the armbands are placed close to each other on the table, a sequence of synchronization context markers $A = \{a_1, \ldots, a_n\}$ can be sensed simultaneously and paired easily. Also, since the signal itself travels at the speed of more than 1.5km/sec, the error is negligible due to this placement.

The time difference between paired context markers from different Myo sensors can be calculated as $d_i = t(a_i) - t(b_i)$, where a_i and b_i refer to the same context marker received by Myo armband a and b. Ideally, these time differences are equal ($d_1 = d_2 = \cdots = d_n$). However, due to communication latency and packet loss, time differences can vary. We assume the time differences D follow a Gaussian probability distribution, and if time differences are not in 90% confidence interval, we consider them as outliers and remove them when calculating average time differences.

We process NTP records using a Theil-Sen Linear Regression [11, 13] to minimize the influence of network status. We then use the slope obtained from the generated Theil-Sen estimator to predict the clock drift of the Myo armband receivers. The synchronization formula for converting a timestamp of receiver A to that of receiver B is :

$$Convert(t_a) = \overline{t_A} - \overline{D} + (t_a - \overline{t_A}) \times \frac{1 - slope_b}{1 - slope_a} \approx t_b \quad (1)$$

4 EVALUATION

We compare the performance of NTP and event-based synchronization approaches with our proposed hybrid approach.

As we did not have ground truth on the true drift for NTP records, we followed recommendations proposed by Li and Sinha [5] and Luo et al. [6]. Hence, we applied linear regression to model true drift. We calculated the synchronization error of NTP records as a difference between the predicted values and observed values.

Table 1: Summary of NTP records from three different Myo armband receivers

Receivers	Error (ms, max)	Clock Drifts (ms, daily)
Macbook Pro (2015)	220	3130
Alienware 15R3	260	320
Alienware 15R4	80	1050

Table 2: Synchronization error for event-based approach and proposed hybrid approach

Hour	Event-based (ms)	Proposed Approach (ms)
0	0.3	0.3
1	99	16
2	246	9
3	329	18
4	408	21
5	531	21
6	627	19
15	1310	18

Table 1 gives the summary of NTP records from three different Myo armband receivers, whose daily time drifts vary between 300 ms and 3130 ms. Due to inconsistent network latency and network congestion, the NTP records contain noise and the maximum error reached 260 ms over the 15-hour experiment, which is less than reported in literature (1800 ms [6]).

For the event-based synchronization approach, the proposed 'hitting the table with the fist' context marker is performed once at the beginning of the experiment to synchronize clocks between two Myo armbands. Due to the different clock drifts of different armband receivers, the accumulated error increases dramatically with time, and Table 2 shows the error increase from 0.3 ms (at the time of synchronization (0)) to 1310 ms (after 15-hour time duration) as compare to ground truth data. Ground truth data in this case is the timestamp from receiver B mentioned in Equation (1).

Compared to the NTP and the Event-based models, the hybrid model has stable performance, and Table 2 shows that the accumulating error is reduced to 20 ms during the 15-hour time period. Figure 3 shows the performance of the event-based model and our hybrid model as compared to ground truth data.

5 CONCLUSION AND FUTURE WORK

In this paper, we propose a method for clock synchronization for multiple wearable sensors. We focus on Myo armbands in particular; however, we argue that our method is also

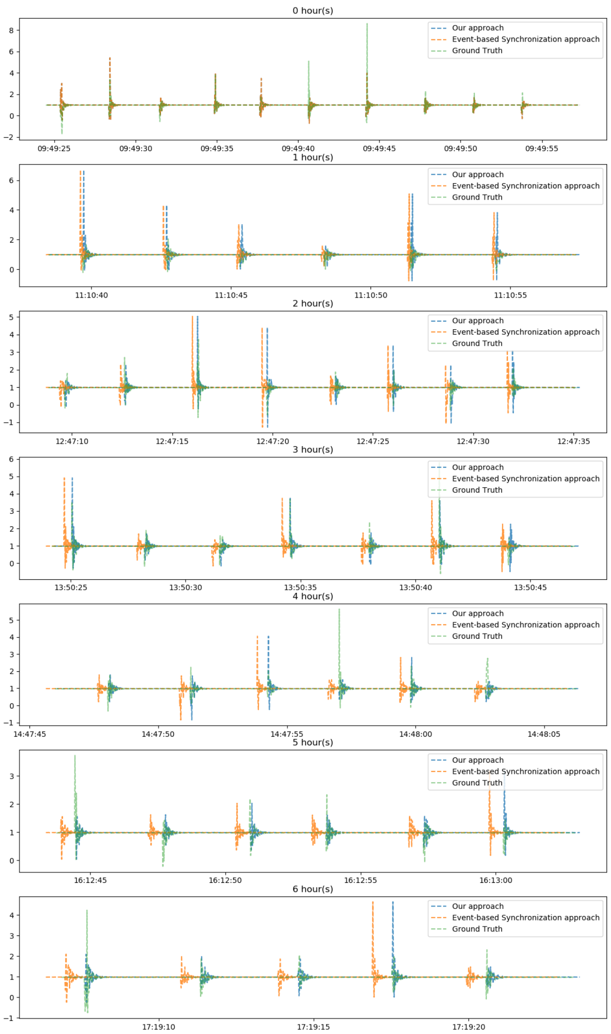

Figure 3: Performance of event-based approach and proposed combined approach as compared to ground truth

applicable to other wearable sensors. We use a combination of NTP and Event-based clock synchronization approaches to minimize the clock drift between multiple sensors and their receivers. During a 15-hour experiment, we show that the error is significantly lower when compared to the individual approaches, and appears saturated. Although, we run our experiment for a short time period (15 hours), we argue and demonstrate that it is enough to register clock drifts. Furthermore, running the experiment for longer time period will not increase synchronization error, as clock drift rates are constant [9].

In the future, we will focus on applying our combined approach on other wearable devices (e.g., Empatica E4 wristband). We also plan to use other clock synchronization methods (e.g., clock synchronization with GPS [3] or Precision Time Protocol (PTP) [2]) to further reduce the synchronization error.

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