Multi-Sensor Data-Driven Synchronization Using Wearable Sensors

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ABSTRACT
This paper presents a method to synchronize the data streams from multiple sensors, including wearables and sensors in the environment. Our approach exploits common events observed by the sensors as they interact. We detect physical and cyber couplings between the sensor data streams and determine which couplings will minimize the overall clock drift. We present a graph model to represent the event couplings between sensors and the drift in the sensor timing and propose a solution that employs a shortest path algorithm to minimize the overall clock drift in the system based on the graph model. Experimental results over two trials show an improvement of 21.5% and 43.7% for total drift and 59.4% and 60.7% for average drift.

Author Keywords
Cyber-physical systems; synchronization; alignment; sensor networks; data-driven.

ACM Classification Keywords
C.3 [**Special-purpose and application-based systems**]

INTRODUCTION
Technological advances are increasing the number of sensors in the environment at a rapid pace, and we will soon be dealing with trillions of sensors and actuators globally [9]. On a smaller scale, smart homes offices, etc. with hundreds to thousands of sensors are becoming a reality [5]. Wearable sensors can be incorporated into smart environments to detect activities [4, 7], and determine location [1, 7].

Given this multitude of sensors, combining data to derive valuable information requires that the sensors have an accurate sense of timing (*i.e.* synchronization) between them. Long-running environmental sensors may be battery powered and therefore, power constrained. Using wireless communication in this situation could lead to shorter battery life. In low-power embedded systems, adding an additional chip for a RTC or a higher accuracy oscillator may not be feasible due to the added cost and power. Collected data is less valuable if it is not well-synchronized. Offline methods are needed to synchronize data from sensors that are independent of specific sensor configurations and can be employed after data collection.

A single event can trigger notable measurements in multiple sensors. We call this concept of shared measurements a "coupling." This coupling could be physical, or cyber. The sensor-data coupling defines an event that occurred at a specific global time. If the local sensor times related to this event are not the same, there is some error in one (or both) of the sensor clocks that needs to be corrected. Environmental sensors are often fixed in a single location. Humans, on the other hand, can move freely throughout an environment. With this in mind, a human with a wearable device can become an "agent" of synchronization in the system.

We present an offline synchronization technique that is applicable to heterogeneous sensor networks to reduce total system drift by using humans with wearable devices as synchronization agents in the environment. We introduce a graph-based method to determine the subset of alignments that best reduces the system drift. The primary contribution of this paper is our novel method of synchronization based on physical or cyber couplings between the sensor data streams. To the best of our knowledge, this is the first investigation with this view of synchronization.

RELATED WORKS
Our technique targets synchronization of data from wearables and sensors in smart environments. Lu and Fu presented techniques for location-aware activity recognition in an outfitted lab with a variety of sensors (*e.g.* pressure sensors, vibration sensors, motion sensors, etc.) to determine activity in an unobtrusive manner through a wireless sensor network (WSN) that is also used for synchronization [10]. Surie et al. also presented a smart home environment that uses WSN for communication and synchronization of sensors [13]. They used 81 sensors on 42 objects to determine activities based on interactions with the subject.

Tapia et al. installed a large number of state-change sensors into two subjects' one-bedroom apartments to detect activities using high-accuracy RTC chips on the sensors and interpolate this data to a reference clock [14]. In all of these scenarios, the researchers control all of the sensors in the

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environment and assume known communication and synchronization protocols for the sensors.

Many synchronization protocols such as the timing-sync protocol for sensor networks (TPSN) [6] and the reference broadcast synchronization (RBS) technique [3] have been developed for wireless sensors networks. These techniques work by sending synchronization messages (TPSN) or reference packets (RBS) to nodes in the network to facilitate synchronization. Several other WSN synchronization methods are based on TPSN and/or RBS with adjustments for energy efficiency [8].

Some techniques use data from wearable sensors to synchronize two sensor modalities. Hardegger et al. [7] and Plotz et al. [12] use specific movements (jumping and hand motions, respectively) from a subject to synchronize wearable sensor data with video being captured.

SENSOR SYNCHRONIZATION

Due to power concerns and operating conditions, sensors in a WSN may not have access to GSM, GPS or another high-accuracy common clock. Without a perfect absolute clock for each sensor, synchronization techniques are necessary. The synchronization and timing issues in sensor nodes are due, in part, to the accuracy of hardware oscillators, which is typically measured in parts per million (ppm).

Oscillator accuracy in WSNs can vary from ±20ppm for a crystal oscillator to ±5000ppm or higher for digitally controlled oscillators (DCOs), voltage controlled oscillators (VCOs), and relaxation oscillators. With this in mind, we estimate the relative drift between two times, t_i and t_j, as

$$d_{i,j} = \frac{ppm(|t_i - t_j|)}{1{,}000{,}000} \text{ where } i \neq j \qquad (1)$$

Sensors and Alignment

A smart home environment can feature a network of environmental and wearable sensors. Let the set of all sensors in the system be denoted as

$$\boldsymbol{S} = \{s_1, s_2, \dots, s_n\}, n \in \mathbb{N}. \qquad (2)$$

Each of the n sensors in the network generates a data stream of *observations*, denoted o_i^n, that include a data value and a corresponding timestamp by the local sensor clock

$$o_i^n = \{x_i^n, t_i^n\}, i \in \mathbb{N} \qquad (3)$$

where x_i^n and t_i^n are the data value and timestamp at the i^{th} index from sensor s_n, respectively.

When multiple sensors in $\boldsymbol{S}$ experience a shared event measurement, or wireless communication, these events happen to the sensors at the same global clock time irrespective of their timestamps. We can leverage these events to synchronize the sensor data streams. Specifically, we search the data streams for evidence of events that are observed by multiple sensors. For example, the opening cap motion found on a wrist worn wearable as well as on the cap of a pill bottle. First, we define alignment points.

Definition: An alignment point is a representation of a physical or cyber event in a sensor data stream that can be accurately distinguished and directly related to the same event in the data stream of another sensor (*i.e.* coupling).

When sensors are physically coupled through proximity of location, we will search for events in their data streams that can be used as an alignment point. We formally describe alignment between two sensors as

$$o_i^k \equiv o_j^l \text{ where } k \neq l. \qquad (4)$$

In an ideal system, $t_i^k = t_j^l$. In real systems $t_i^k \neq t_j^l$ and a drift exists. We determine the times related to the data points selected to generate a set of alignment points denoted as

$$\boldsymbol{A} = \{(o_i^k, o_j^l) | \exists i, k, j, l \text{ such that } o_i^k \equiv o_j^l\}. \qquad (5)$$

Each alignment point in $\boldsymbol{A}$ includes the relevant observations from a pair of sensors. Once alignment points are found in the sensor data streams, the sensor times can be adjusted to reduce drift. Template and entropy based methods to determine alignment points have been presented previously for sensor pairs [2]. We expand on these concepts for multiple sensors below.

Multi-Sensor Synchronization Formulation

We want to select the subset of alignment points from the set of alignment points, $\boldsymbol{A}$, defined in (5) that create the greatest reduction in total system timing error (*i.e.* drift). To accomplish this, we define a graph model of the system

$$G = (V, E_a \cup E_d). \qquad (6)$$

where the vertices, V, represent the observations from each alignment in $\boldsymbol{A}$, edges, E_a, represent the alignments (*i.e.* coupling between two observations), and edges, E_d, represent the drift between observations on a single sensor.

Figure 1 shows a sample graph with a global clock and four sensors. Because we define alignment points between a pair of sensors, each alignment point is represented by two vertices and one edge in the graph. Therefore,

$$|V| = 2|\boldsymbol{A}| \text{ and } |E_a| = |\boldsymbol{A}|. \qquad (7)$$

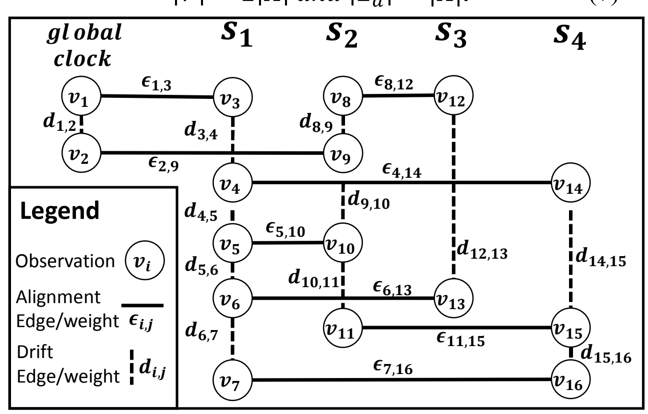

Figure 1: Sample graph model with alignment and drift edges for 4 sensors and the global clock.

We sort the vertices by sensor and time to generate a multi-level bipartite graph. Each edge, $e_{i,j}$ connects vertices, v_i and v_j. Each of the edges in E_a also has a weight, $\epsilon_{i,j}$, based on the estimated alignment error

$$\forall\ e_{i,j} \in E_a, weight = \epsilon_{i,j}. \quad (8)$$

The edges in E_d have a weight, $d_{i,j}$, based on the drift between observations described as

$$\forall\ e_{i,j} \in E_d, weight = d_{i,j} \quad (9)$$

where $d_{i,j}$ is the relative drift between v_i and v_j given that v_i and v_j are vertices representing consecutive observations on a single sensor calculated as described in (1).

Each column in the graph shown in Figure 1 represents a sensor in the network. The solid horizontal lines represent the alignment edges, and the vertical dashed lines represent the drift edges. The time at each vertex is defined as

$$t_{v_i} = t_{global,v_i} + d_i \quad (10)$$

where t_{global,v_i} is the true global time at the vertex, d_i is the total drift at the vertex, and t_{v_i} is the locally reported time for the vertex.

The total drift at each vertex in the graph can be determined by 3 possible factors. In Figure 1, the neighbors of vertex v_9 are v_8 and v_{10} on the drift edges and v_2 for the alignment edge. The drift at v_9 would be determined by the minimum edge weight of the neighbors and node drift of the neighbors. We make the following observation:

Observation 1: The total drift at each vertex v_j is dependent on its neighboring vertices and is calculated as

$$d_j = min(d_l + \epsilon_{j,l}\,, d_i + d_{i,j}, d_k + d_{j,k}). \quad (11)$$

We defined our relative drift estimates in (1). The elapsed time that the clock has been running must be known to estimate the relative drift. This time difference is maintained by each sensor. Therefore we make another observation:

Observation 2: Every vertex in the graph must have a path to the global clock.

Our goal is to minimize the drift at each vertex to ensure the time is as close to the global time as possible. This means we must select the subset of alignments to reduce the total drift at each node. This objective is mathematically stated as

$$\widehat{E_a} \subset E_a | minimize \sum_{i=1}^{|V|} d_i. \quad (12)$$

To solve this problem, we make one additional observation.

Observation 3: The global clock can be treated as an ideal clock source with $0\,ppm$ accuracy so all global clock vertices have total drift $d_i = 0$. Also, all relative drifts, $d_{i,j}$, between global clock vertices will be 0.

We take advantage of the weighted graph and our earlier observations to guarantee the optimal ordering of local decisions. Based on Observation 3, all global clock nodes can be viewed as a single node. Observation 2 says every vertex in the graph has a path back to the global clock. Finally, Observation 1 says that the total drift at each vertex is influenced by the drifts of the neighboring vertices and the weights of their edges. Therefore, starting at the first global clock vertex, we find the shortest path to all sensor vertices. The shortest path to each vertex indicates the best set of edges such that the drift at that vertex is minimized. This allows us to determine $\widehat{E_a}$ and the order to minimize the total drift in the system.

EXPERIMENTS AND RESULTS

We conducted two trials of experimental validation. In each trial, we had two subjects wear a custom IMU sensors on the wrist of their dominant hand. Sensors were also attached to a door, a pill bottle, and a cup in the environment. The custom sensor nodes included a 3-axis gyroscope and 3-axis accelerometer collecting data at 200Hz. Trial 1 lasted three minutes and Trial 2 lasted five minutes. MATLAB was used to process the experimental data.

Results and Analysis

Trial 1 produced a graph with a total of 42 vertices, 21 alignment edges (E_a), and 32 drift edges (E_d). Trial 2 produced a graph with 46 vertices, 23 alignment edges (E_a), and 40 drift edges (E_d).

The subjects using the wearables are being used as the synchronization agents. Therefore, we use a crystal oscillator for the timestamps on the wrist-worn sensors and a DCO for the timestamp on the sensors in the environment. We estimate that the Bluetooth error as $13ms$ [11] and the entropy and template based alignment error as $52ms$ and $132ms$ [2] respectively. We use $20ppm$ and $5000ppm$ for the wearable and environmental sensor stability respectively. We calculate the drift for the graph vertices using the crystal oscillator as the gold standard.

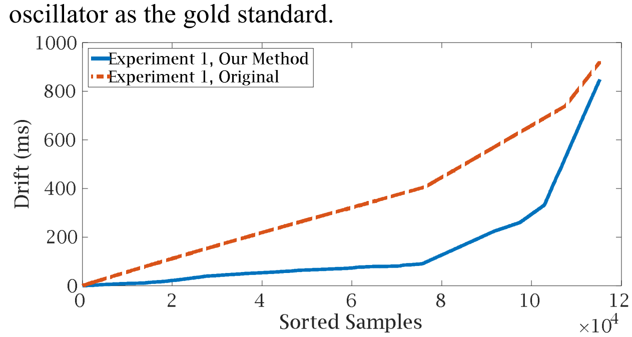

Figure 2: Trial 1 environmental sensor time data sorted from minimum to maximum drift.

Figure 2 shows the drift from the environmental sensors for synchronized (our method) and unsynchronized (original) data for Trial 1. We calculated the drift at each sample and sorted from minimum to maximum drift. Though the maximum drift for the synchronized and unsynchronized data are close, it can be seen that the synchronized data has less overall drift and more samples with low drift.

Table 1 shows the total drift results from each trial at the observations, as described in (12), and the average drift for all sensor data. Our method improves the total system drift by 43.7% in Trial 1 and 21.5% in Trial 2 when considering the observations. We linearly interpolate the timing data between the observations on each sensor to reduce the drift on the entire data stream. When looking at the average drift across the data on the environmental sensors, the drift is reduced by 59.4% in Trial 1 and 60.7% in Trial 2.

Metric	Sensor Data w/Alignment (our method)	Sensor Data w/o Alignment (original)
Trial 1: $\|V\| = 42, \|E_a \cup E_d\| = 53$		
Total Drift	$2{,}405ms$	$4{,}270ms$
Average Drift	$140.9ms$	$346.6ms$
Trial 2: $\|V\| = 46, \|E_a \cup E_d\| = 63$		
Total Drift	$4{,}981ms$	$6{,}344ms$
Average Drift	$194.8ms$	$495.8ms$

Table 1: Total drift at observations and average drift results based on all data points and timestamps

CONCLUSION

We presented an alignment and synchronization technique for a smart environment using human subjects with wrist-worn sensors as the agents for synchronization. Using the physical interactions between the subjects and the environment and sensor clock accuracy estimates we developed a graph model to determine a subset of alignments to reduce the total system drift and the average system drift. The algorithm shows a decrease in average drift of approximately 60% for the trials.

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