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Wireless Multi-sensor Physio-Motion Measurement and Synchronization System and Method for HRI Research

Chuanchu Wang, Haihong Zhang, Soon Huat Ng, Xiaoqun Zhu, Kai Keng Ang

***Abstract*— There is a strong demand for acquisition, processing and understanding of a variety of physiological and behavioral signals from the measurements in human-robot interface (HRI). However, multiple data streams from these measurements bring considerable challenges for their synchronizations, either for offline analysis or for online HRI applications, especially when the sensors are wirelessly connected, without synchronization mechanisms, such as a network-time-protocol. In this paper, we presented a full wireless multi-modality sensor system comprising biopotential measurements such as EEG, EMG and inertial parameter data of articulated body-limb motions. In the paper, we propose two methods to synchronize and calibrate the transmission latencies from different wireless channels. The first method employs the traditional artificial electrical timing signal. The other one employs the force-acceleration relationship governed by Newton's Second Law to facilitate reconstruction of the sample-to-sample alignment between the two wireless sensors. The measured latencies are investigated and the result show that they could be determined consistently and accurately by the devised techniques.**

Index Terms— HRI; EEG; EMG; IMU; Time Synchronization

I. Introduction

Towards highly intelligent human-robot interfaces, to acquire, process and understand a variety of physiological and behavioral signals from the measurements of humans' mental and physical processes becomes critically important [1]. Specifically, human's motion intent can be manifested in complex data patterns embedded in multiple data streams including electroencephalogram (EEG) [2], electromyogram (EMG) [3], kinematics measurement (often by Inertial Measurement Units [4], and optical trackers) and force sensor data [5]. In the meantime, multiple data stream brings a considerable challenges to data synchronization both for offline analysis and online applications [6]. Especially, the variety of sensors commercially available usually come with different sampling rates but no mechanism for network-time-protocol. This poses a serious problem to data processing and machine learning to capture the underlying intrinsic yet non-stationary associations of the measured signals.

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C. Wang, H. Zhang, S. H. Ng, X. Zhou and K. K. Ang are with Institute for Infocomm Research, Agency for Science, Technology and Research (A*STAR), 1 Fusionopolis Way, #21-01, Connexis, Singapore 138632 (email: {ccwang, hhzhang, shng, zhouxq, kkang}@i2r.a-star.edu.sg)..

K.K. Ang is also with the School of Computer Science and Engineering, Nanyang Technological University, 50 Nanyang Ave, 32 Block N4 #02a, Singapore 639798 (email: kkang@ntu.edu.sg).

In this paper, we report on a wireless multi-modality sensor system, primarily comprising an OpenBCI [7] based solution for biopotential measurements such as EEG and EMG; and a Shadow Motion Capture Kit [8] for inertial measurements of articulated body-limb motions; and accessory sensors. Both OpenBCI and Shadow Motion Kit perform data transmission with a computer wirelessly through different channels, and they inherently operate on different clocks and different sampling rates.

To synchronize precisely the data samples through the two (or more) WIFI channels, we have tested two methods. The first method is similar to the existing solutions, i.e., using an apparatus to generate alternating electrical waves switching between two levels, and the software processes the received signals from the measurements and compares the detected events therein with the true event timing measured by the computer clock. The other method relies on Newton's Second Law using the force-acceleration relationship. Specifically, biopotential instrument is utilized to measure the force (through a force-electricity transducer) applied to the IMU, and, meanwhile, the IMU is used to measure the acceleration. The force-acceleration relationship thus allows us to reconstruct the sample-to-sample alignment between the two sensors.

Several groups of different tests are carried out to investigate the measured latencies and confirm that they can be consistently and accurately determined. The two techniques perform a precise alignment of biopotential measurements and inertial measurements to an accuracy level of 10ms – the sampling interval of the inertial measurement. The latency of the wireless biopotential measurement alone varies with the change in the sampling rate, but can be accurately determined at 3-millisecond standard deviation level.

II. System Design

A. Multimodality sensor data acquisition system

The system design emphasizes real-time signal measurements -- acquisition and computer pre-processing. As depicted in Figure 1, the whole system comprises a bio-potential measurement device, a human body-motion capturing device, and a data acquisition controller and synchronization system running on a laptop PC.

The fully wearable sensors include a) EEG/EMG electrodes, amplifier module and transceiver module included in the OpenBCI kit; b) body motion sensors including IMU (inertial measurement units) and foot-attached force sensors. These sensors and transceivers are battery powered, allowing fully ambulatory uses. This is important for human-robot interaction applications.

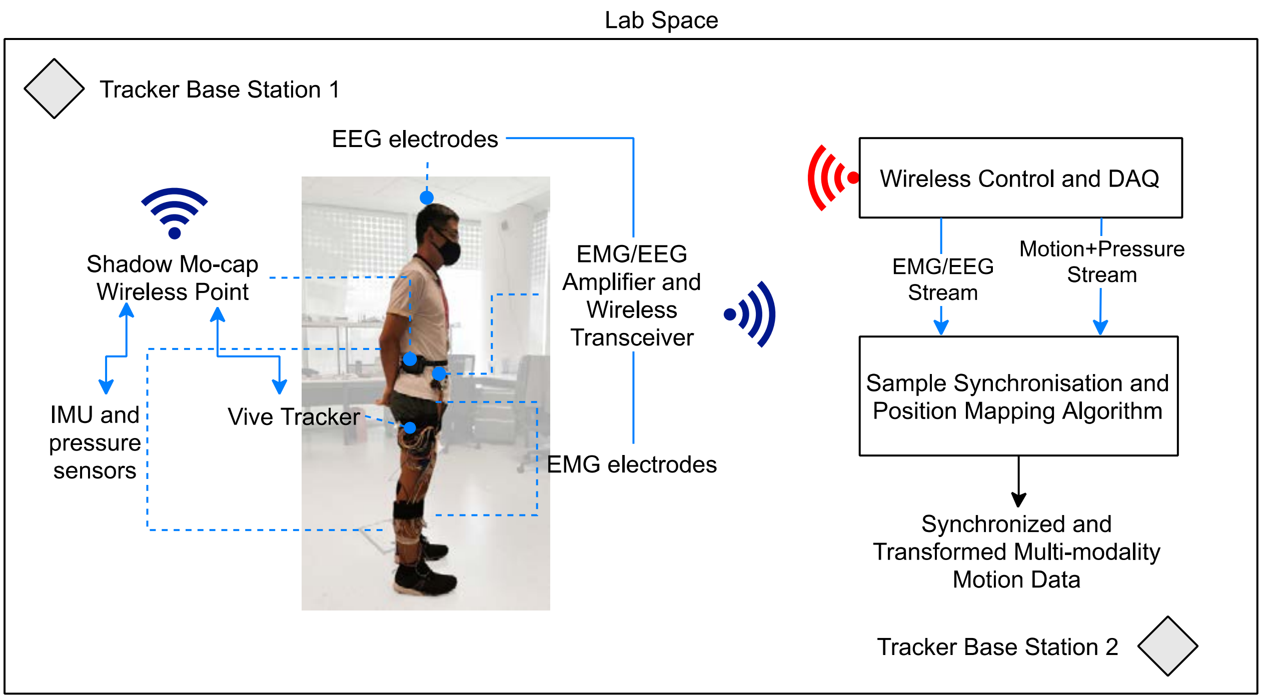

Figure 1: System Diagram. With a WIFI based mobile OpenBCI device attached to participants' legs to detect EMG signals, a WIFI based mobile Shadow Motion system to detects the movements of body parts and foot pressure, and a VIVE tracker determines the global position, all data sent to a PC via WIFI for recording.

The body motion sensors and the transceiver as well as data acquisition and display software are provided as a Shadow Motion Capture system from the *Motion Workshop*. The Shadow system provides not only the body posture data estimated from the IMU data, but also the raw IMU measurements. Additionally, the system includes two insole units, for the left and the right feet respectively, that each measures the pressure force at the toe and the heel positions. Data are recorded at 100 Hz.

Two tracker base stations were set up in the lab space that, when worked with a wearable tracker (*Vive Tracker*), provides absolute 3D positioning data. On the other hand, the wearable IMUs of Shadow provide body motion data in the local coordinate system (with respect to the "anchor" point on waist).

For measurement of EEG and EMG signals, we choose the OpenBCI device, as shown in Figure 2. With OpenBCI's Cyron and Daisy modules connected together, the system supports up to 16-channel bipolar bio-potential measurements, each channel consist of a pair of vertical pins connecting to the middle and end of a muscle to measure the EMG signal.

For data transmission to the computer, a WIFI shield is added to the board (Figure 2b). The OpenBCI-GUI software from supplier provides the functionalities to locate the IP address of the WIFI module from the intranet, to configure system parameters, such as number of channels, sampling rates, etc., and to provide mechanisms to transfer EEG/EMG data to application systems through LSL. In our system, instead of using OpenBCI-GUI as a middleware for data transmission, direct TCP/IP communications with the WIFI module for device control and data inquisition are created, so that the system latencies are minimized as much as possible.

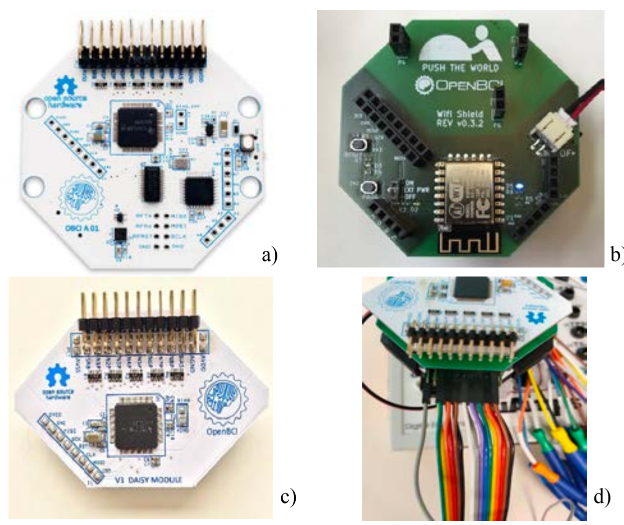

Figure 2: Bio-potential measurement device: a) Cyton board the main board to acquire 8 channels data, b) WIFI shield, c) Daisy module with 8 more channels, d) Integrated amplifier-transceiver unit for EMG.

B. Multi-modal data synchronization mechanism

As mentioned earlier, the different modalities of the sensor modules are operated on two individual clocks and different WIFI connections. Due to the considerable variability in the latency of WIFI transmission and processes in hardware and software operations, one could not use the raw data samples at the receiving end (computer software) to infer the relative timestamps of each sample directly. Therefore, the synchronization mechanism is designed to re-build data sample streams in real time, such that the reconstructed data samples can be precisely aligned across different modalities – including the computer's own clock system.

The mechanism works in two phases: 1) calibration phase, and 2) online processing phase.

The calibration phase is critical as it measures the latency times and the actual sampling rates, and the measured latency times for each sensor can then be used to compensate the latency during online processing.

The key in building a latency measurement device is creating special transient events that can be captured and detected at a high time-resolution by the various sensors. Thus, we have devised a solution that works by measuring artificially generated abrupt accelerations. Particularly, we firmly attach a vibration force sensor to the IMU unit, and link the force sensor to one of the EMG/EEG channels. The acceleration here is generated by applying a force abruptly (knocking) to the sensor. The fast-response force sensor transduces the force measurement into electrical potential, which in turn can be captured by the biopotential measurement instrument (OpenBCI EEG/EMG channel). At the same time, the acceleration signal is picked up by the IMU's accelerometer. By jointly analyzing the received measurements of the same force (by the EEG/EMG sensor) and that of its instantaneous effect, i.e. acceleration (through IMU), we can then compute the statistics of the relative latency between the two sensors.

In addition, the computer locks in the samples' arrival times measured by the computer clock from both devices. This allows us to analyze the latency as well as the actual sampling rates. For precise measurement of actual sampling rate and latency, we have also devised a method to generate a special electrical waveform: the system uses a waveform generator (a MCU board) to create alternating electrical potential levels, and links the output to the OpenBCI board's input port reserved for event-marking. Particularly, the system toggles the output potential between two levels regularly (in our system, the frequency is 1 Hz). The toggle events especially the timing information measured by the computer clock are logged and later compared with the received measurement from the OpenBCI board for precise latency and sampling rate analysis.

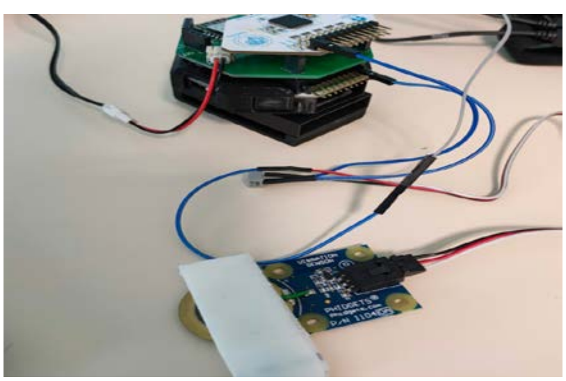

Figure 3: Vibration force sensor based latency calibration for data synchronization.

The vibration force sensor is from Phidgets. It uses a piezoelectric transducer to an generate electric in response to applied mechanical stress. As the output is not compatible with the of the acquisition board, a simple voltage divider circuit is added between the output of the sensor and the input of the acquisition board to make it compatible (Figure 3).

III. Test Data Acquisition and analysis

We have collected some testing data for offline analysis to study the latencies of our settings. The study protocol using healthy human subjects had been approved beforehand by the ethics review board of Agency for Science, Technology and Research, Singapore (IRB Ref. No. 2020-006).

A. Biopotential instrument sampling rate and latency calibration

Using the above-configured system, we recorded three data files while running the bio-potential amplifier at different sampling rates: 250Hz, 500Hz, or 1000Hz. Figure 4 shows two signals: the blue line represents the received signal of the marking channel (see Section II.B) in the y-axis versus the sample arrival time in the x-axis. The vertical straight blue lines represented the event-triggered toggles of the electrical signal. The red-color diamond marks the algorithm-detected points where the blue colored signal pass through the 0-value line.

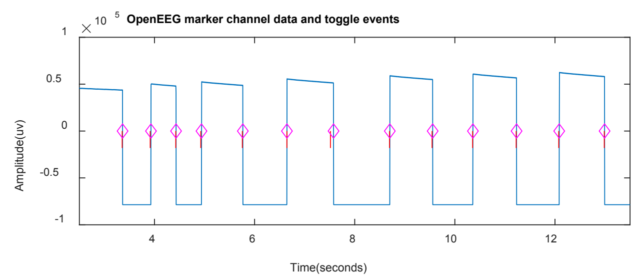

Figure 4: Biopotential sensor latency test. Blue solid line: the received signal; red-color vertical bars: the toggle events; the red-color diamond shaped markers: detected toggle events in the arrived measurement samples.

Therefore, the latency is the time interval between the red bars and red-color diamonds.

Table 1 lists the statistics of our latency test results. The latency is around 10 milliseconds and it is small enough for our application.

Table 1: Latency tests for 3 sampling rates

Sampling Rate (Hz)	Mean (ms)	Std (ms)
250	14	17.7
500	9	4.1
1000	8.9	3.4

B. Inter-sensor latency

We conducted a total of 9 rounds of recordings of a sequence of "knocking" events in both the biopotential instrument (OpenBCI) and the IMU sensor (Shadow Motion), as described in Section II.B) with a sampling rate of 500Hz and 100 Hz, respectively. Figure 5 shows one of the recording. The x-axis denotes the sampling arrival times of the measurements. The red color line shows the force-turned-electrical-potential measured by the OpenBCI board. The numbers (1 to 20, showed 1-7 only) mark the detected maximum forces. The blue color line shows y-axis acceleration values measured by the IMU sensor, as the "knocking" was primarily in the y direction. The maximum points of acceleration, i.e. the primary peaks, are marked as blue-color numbers. Since the force is linearly related to the acceleration according to Newton's Second Law. The two sequences of detected maximum acceleration and maximum force can be associated to determine the relative latency between the two sensors.

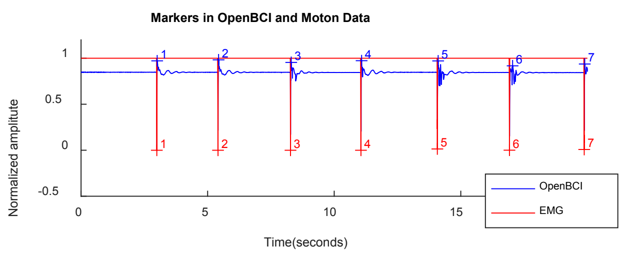

Figure 5: Event matches between vibration sensor in recorded OpenBCI data (red) and accelerometer sensor in the motion data (blue).

Figure 6 illustrates the statistical analysis of the latency.

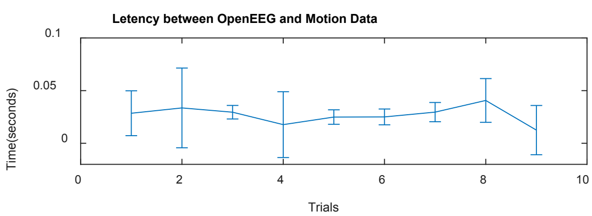

Figure 6: Relative IMU-Biopotential sensors data latency (the mean value as the curve, and the standard derivation as the added vertical bars)

The grand mean of the relative-latency is approximately 30 milliseconds. Considering that the motion data sampled at 100Hz, and this is about 3 - 6 samples differences. The apparent standard deviation varied from as low as ~10ms to ~50ms, while averaging ~20ms. This could be, by a large extend, attributed to the variation in sampling arrival time latency in the biopotential measurement (see Table 1) and that in the IMU data.

While the IMU data's latency could not be measured so far as precisely as that for biopotential measurement, the two measurements are both using WIFI connections to transmit data. Hence, we can refer to Table 1, which shows that for a sampling data stream at 250Hz, the standard deviation of transmission latency is 17.7ms. Hence, the variation measured in the relative-latency between two sensor data streams are very comparable and expected, which suggests that the ~30ms inter-latency is approximately the actual latency – which is actually consistent across different trials: deviated by 10ms only – or just 1 sample in motion sensor data.

IV. CONCLUSION

In this paper, a wireless multi-modality physio-motion sensing system for human-robot interfacing research has been developed and studied. The system requires precise synchronization between multiple sensors data in real-time. A sensing system using the OpenBCI solution for wireless bio-potential (EEG and EMG) measurements and the Shadow Motion system for wireless inertial measurements has been established. The hardware+software mechanisms, the methods to calibrate the true sampling rates and the latencies from sampling to data receiving by the computer software through WIFI connections have been developed.

Our experimental results suggest that the biopotential measurement has a latency that varies with the sampling rate, and reaches below 10 ms mean latency at or beyond the 500Hz sampling rate, while the standard deviation of the latency can be as low as 3.4 ms for the sampling rate of 1000Hz. Thus, by using our calibration protocol, the wireless biopotential measurements can be determined to a timing accuracy of better than 10 ms.

Using our joint force-acceleration measurements, the relative-latency between the biopotential measurement and the inertial measurement can be estimated at approximately 30 ms, with a very small variation (a single inertial measurement interval) across different repetition of the test.

Given the measured latency and variations, the developed methodologies allow the system to be associated with inertial and biopotential measurements accurately in a full wireless setup, which could facilitate the research and development of high-performance human-machine interfaces.

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