Complementary Use of Wearable Technology 3: Temporal Alignment and Similarity Measures of Accelerometer Signals from Two IMU Devices

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Headline

As noted in our earlier papers (16, 17), sports scientists often collect data from more than one wearable device. We showed that combining data from different wearable devices can provide valuable information regarding player training load and rehabilitation status. An important aspect of this work was temporal alignment of the data from the two different devices, ensuring that the data collected reflects the same activities of interest. In those papers, data were aggregated, examined and compared over relatively long, time intervals (e.g., several minutes).

The STATSports APEX device receive its initial time stamp at start-up via communication with GPS satellites. On the other hand, the IMeasureU Blue Trident sensor (BT-IMU) is started using a phone app and Bluetooth communication. Thus, it receives its initial time stamp via the phone clock. As a result, a small, time delay can be introduced into the BT-IMU data (1, 15). This is often considered negligible when focusing on data that is aggregated over several minutes (16, 17). When comparing raw accelerometer signals during short time intervals (such as the stance phase of a single step), this delay can be problematic. Thus, temporally synchronizing time series data from different wearable devices is critical. In addition, when comparing the same variables from different devices (e.g., acceleration), it is important that each sensors' data be congruent, ensuring data from one sensor is equivalent to those of others.

Cross-correlation is a numeric approach by which the degree of similarity between two signals as well as temporal alignment differences can be quantified (3, 5). It has long been used to determine time delays between regularly sampled signals (5). In simple terms, this method correlates to two signals then shifts or lags one signal with respect to the other and repeats the correlation. This generates a cross-correlation function (CCF), plotting lag times versus correlation coefficients. The peak of this function (CCF_{max}) represents the similarity or congruency between the two signals. The lag associated with CCF_{max} represents a time delay (TD) in one signal with respect to the other and can be used to temporally align the signals. Previous work using multiple body-worn accelerometers show that this is a useful approach to evaluate performance by different devices (4, 6, 19, 20).

Aim

The first aim of this project was to use cross-correlation to temporally align accelerometer signals from the APEX and BT-IMU sensors. The second aim was to evaluate similarity of the accelerometer signals obtained from the two devices.

Methods

Technology

As previously described (16, 17), two types of IMU sensors were used. The STATSports APEX GPS/IMU (18 Hz GPS, ±200g 952 Hz tri-axial accelerometer, 952 Hz gyroscope and 10 Hz magnetometer) and the IMeasureU Blue Trident (BT-IMU) IMU (±16 g 1125 Hz and ±200 g, 1600 Hz accelerometers, 1125 Hz gyroscope and 112 Hz magnetometer). All devices were turned on 30 min before each session. Data collection by the BT-IMUs was initiated via the IMU Step phone app. After each session, data from the APEX and BT-IMU devices were downloaded using the manufacturer's software (SONRA and IMU Step, respectively). Sessions were split into individual drills or events. Raw data were then exported to individual .csv files for further analysis. All subsequent analyses were performed using custom written MATLAB programs.

Controlled Impact Study

The first study utilized simultaneous, controlled impacts applied to both the BT-IMU and APEX devices. Two BT-IMU and one APEX unit were attached to a device similar to a movie "clapperboard". The clapperboard was used to simultaneously apply 4-5 impacts to all three devices. This was done using eight APEX units and eight BT-IMU sensors, resulting in 24 BT-IMU sensor comparisons and 48 BT-IMU vs APEX comparisons. Trials were conducted using three sensors to replicate their use in the field with athletes, e.g., two ankle-mounted BT-IMU devices and one trunk-mounted APEX device. Impacts were delivered within 15 min of start-up, then again after a period of approximately 2 hrs (to determine accelerometer drift during a typical session).

Running Study

The second study examined accelerometer signals obtained during running. Participants for this study were four collegiate female soccer players (age, 19.0 ± 0.8 years; height, 161.0 ± 5.4 cm; weight, 56.8 ± 2.2 kg). Institutional review and human subjects use approval was acquired before commencement of the project. All data were collected during regular team training sessions. Subjects were asked to perform running trials ranging 100 to 400m in length and at speeds ranging from a jog to a sprint (8-25 km/hr).

Prior to and immediately after training three impacts were delivered to the APEX and BT-IMU sensors (as described above). Data from these impacts were later used to temporally align sensor data collected during the running bouts. The APEX unit was then placed in the pouch located on the back of a STATSports provided vest (similar to a sports bra). This situated the device on the trunk at the level of the upper thoracic vertebrae. Two BT-IMU sensors were also placed inside the STATSports vest, held securely against the APEX device. After each session, controlled impacts were again delivered to the three devices. This was done to check for potential time-dependent drift.

Signal Processing and Statistics

For each sensor, the .csv file contains the timestamp of each sample (in UNIX epoch time) along with the tri-axial accelerometer data. Triaxial accelerations data were converted into resultant acceleration (a_r) using the relationship: $a_{r^2} = a_{x^2} + a_{y^2} + a_{z^2}$, where a_x, a_y and a_z represent accelerations in the anteroposterior, longitudinal and mediolateral directions, respectively. The a_r data were used in all subsequent analyses.

A four-step procedure was used to temporally align accelerometer data. First, since the APEX and BT-IMUs collect data at different frequencies, a_r signals from the APEX accelerometer and the BT-IMU ±200g accelerometers were re-sampled to a consistent frequency of 1000 Hz using the MATLAB $< resample >$ function (9). Next, the re-sampled signals were filtered using a fourth order, low-pass Butterworth filter (40 Hz) $< filtfilt >$ (10). Third, cross-correlation was performed on the APEX and BT-IMU signals using the $< xcorr >$ function with the $< coeff >$ normalization option (this normalizes the CCF sequence so that the autocorrelations at zero lag are equal to 1.0) (7). For each CCF, CCF_{max} was determined as the first local maximum to the right of zero-lag and represents the similarity between signals. The time delay (TD) between signals was taken as the lag associated with CCF_{max}. Finally, the BT-IMU signal was aligned with the APEX data by using the TD to shift the latter ahead in time and then removing unnecessary data from the end of the former.

To verify the TD values, non-aligned data from the controlled impact study were used. The MATLAB $< findpeaks >$ function was used (8) to determine the magnitude and location of each device's acceleration (a_r) peak. Locations of the peaks were the compared to the TD values obtained through cross-correlation analysis.

Similarity between the BT-IMU and APEX sensors were evaluated two ways. First, the CCF_{max} values obtained through cross-correlation (controlled impact and running studies) were evaluated. Second, acceleration peak magnitudes found in the controlled impact study were compared between devices.

Bland-Altman plots and Pearson Product-Moment correlations were used to compare values obtained from the APEX and BT-IMU sensors.

Results

Controlled Impacts

An example of accelerations during a controlled impact is shown in Figure 1. As can be seen, the BT-IMU signals lag behind the APEX signal by about 160-165 msec while the two BT-IMU signals are very closely aligned. The shape signals and the peak accelerations appear to be very similar.

Example CCFs for the APEX sensor and two BT-IMUs during controlled impacts is shown in Figure 2. The CCF of the two BT-IMU comparison is centered near zero with a TD of 0.001 and a CCF_{max} 0.998. In contrast, the two CCFs for the BT-IMU versus APEX comparisons are shifted to the right indicating. This indicates that BT-IMU signals "lag" behind the APEX. In this example, the TD values were 0.160 and 0.161 sec and the CCFmax values were 0.982 and 0.985.

Mean CCF_{max} values for the impact study were quite high between the two BT-IMU sensors (Table 1). They were also high when comparing BT-IMU sensors to the APEX device. This indicates the signals generated by the two types of sensors have high similarity and suggests high inter-device reliability.

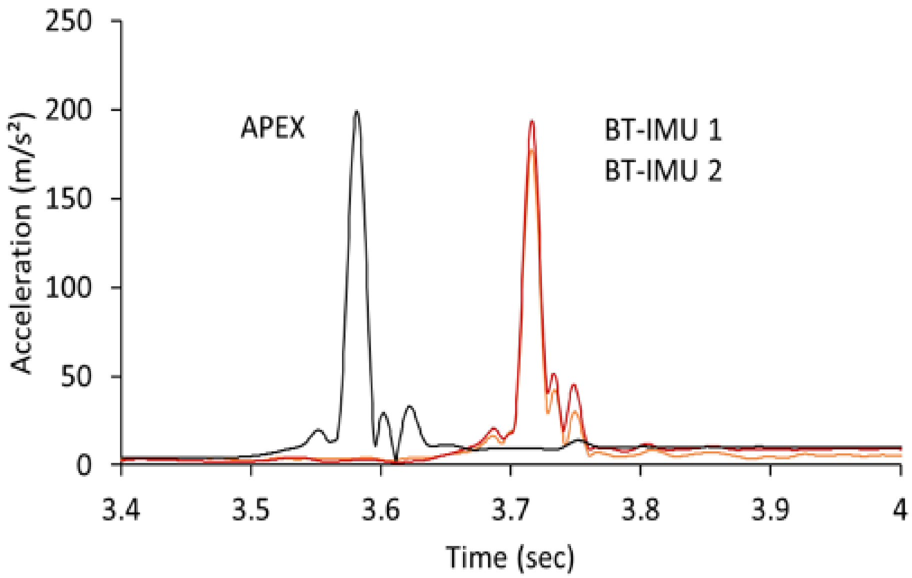

Fig. 1. **An example of accelerometer signals obtained during a controlled impact. The APEX signal is shown in black and the two BT-IMU signals are shown in red and orange.**

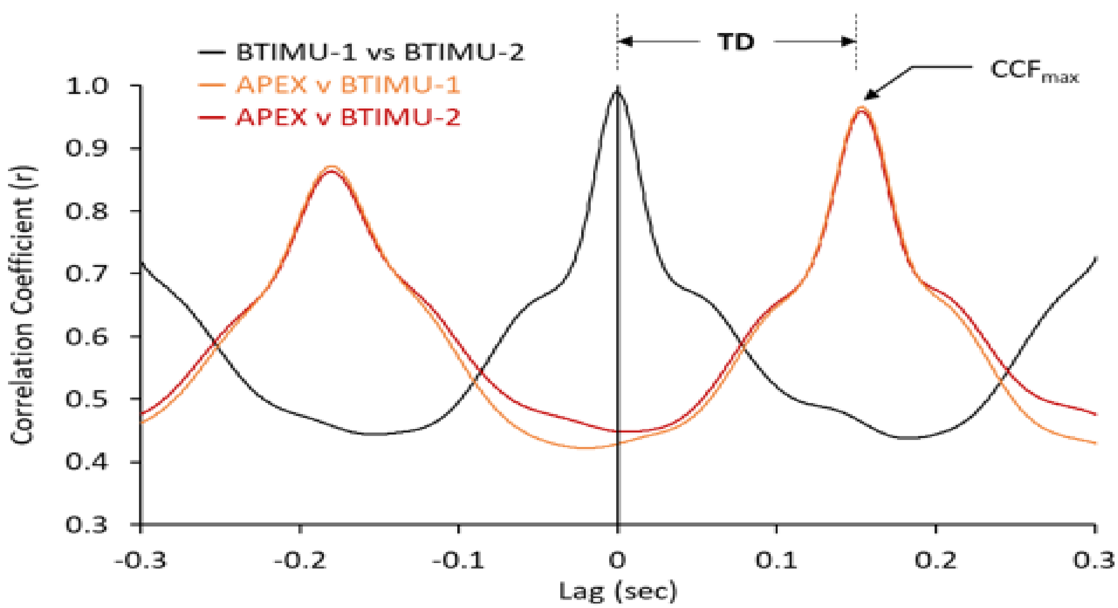

Fig. 2. **A typical CCFs obtained during a series of controlled impacts. Determination of the CCFmax and TD are also shown.**

Table 1. Cross-correlation analysis of accelerometer signals during controlled impacts. Pre: measures taken at the start of training. Post: measures taken at the end of training (~2 hrs).

	BT-IMU1 vs BT-IMU2	BT-IMU1 vs APEX	BT-IMU2 vs APEX
CCF_{max} (r)			
Pre	0.987 ± 0.014	0.930 ± 0.033	0.923 ± 0.030
Post	0.985 ± 0.021	0.936 ± 0.032	0.931 ± 0.029
TD (sec)			
Pre	0.000 ± 0.001	0.152 ± 0.036	0.152 ± 0.035
Post	0.000 ± 0.001	0.153 ± 0.033	0.152 ± 0.038

Values are $\bar{x}$ ±SD

Table 1 also shows TDs between the BT-IMU units were very small (Table 1). In two-thirds of comparisons, TDs were zero and exceeded two points or 2 msec in only two cases. For the IMU – APEX comparisons, the IMU signals lagged behind those of the APEX device. TD values were somewhat variable, ranging between 101 and 300 msec with an average of ~152 msec (Table 1).

The cross correlation analysis also showed that the TD between devices did not change from before to after the training session (approximately 2 hrs). The correlation coefficient between the pre- and post-training CCFmax was 0.999 and Bland-Altman bias was 0.001%.

Analysis of peak accelerations provided a second evaluation of sensor lag time as well as inter-unit reliability. Acceleration peaks recorded during the controlled impacts are shown in Figure 3. The Pearson correlation coefficient between the BT-IMUs and APEX sensors was 0.979 and 0.978 while the r-value between the two BT-IMUs was 0.991. The Bland-Altman analyses showed a bias of -0.963% between the BT-IMU and APEX devices with upper and lower limits of agreement of -8.423 and 6.500%. Also, timing of the acceleration peaks detected by the IMU sensors trailed those of the APEX units by 0.155 ± 0.024 sec, a value close to TDs reported in Table 1. Overall, the results of the controlled impact study suggests that acceleration signals from the APEX and BT-IMU can be temporally aligned and show high similarity.

The second phase of this study focused on running activity. A segment of raw accelerometer signals obtained from one BT-IMU and one AEPX sensor are shown in the top panel of Figure 4 (for clarity, the second BT-IMU signal is not shown). Similar to Figure 1, the BT-IMU signal is delayed compared to that of the AEPX. Cross correlation analysis of the entire 22 sec of data resulted in a CCF_{max} of 0.973 and TD of 0.161 sec. The TD was then applied to the BT-IMU signal, shifting it forward in time (Figure 4, bottom panel). Applying the TD to the BT-IMU results in the two signals overlapping with considerable congruence.

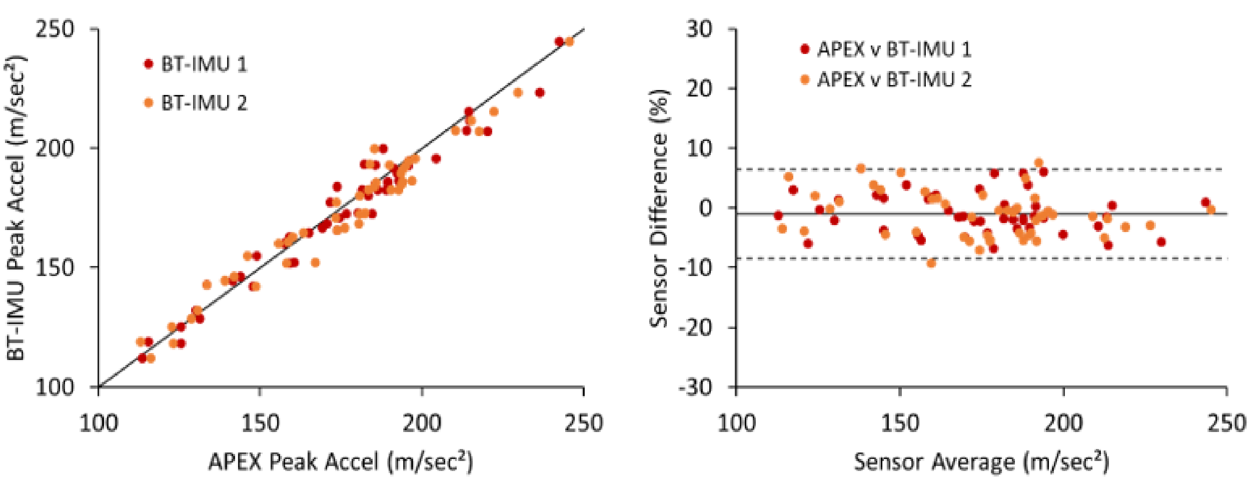

Fig. 3. Left: Relationships between peak acceleration values obtained from the BT-IMUs and APEX sensors. Right: Bland-Altman plots showing differences between peak acceleration values detected by the two sensor types.

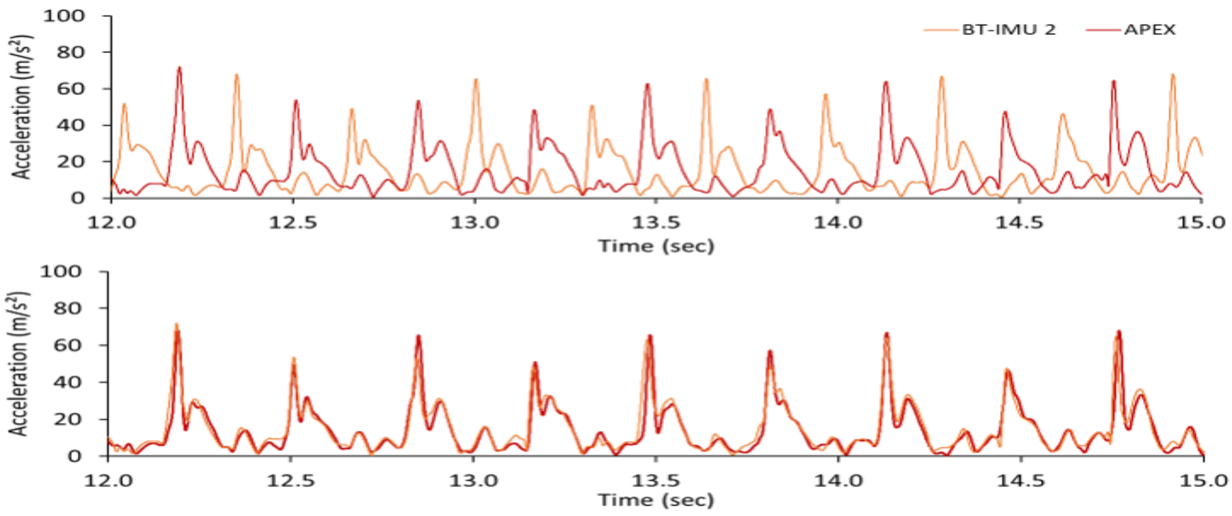

Fig. 4. Top: Raw APEX and IMU signals recorded during running. For clarity only one IMU is shown (orange) along with the APEX signal (red). Bottom: APEX and IMU signals after shifting the IMU signal using the derived time delay.

Mean CCF_{max} and TD values for all of the running trial are shown in Table 2. The values shown here are consistent with those shown in Table 1. They indicate a high degree of signal similarity between the BT-IMU and APEX devices during running. Also, while there was some variability in TD between sensor parings, the mean TD for BT-IMU and APEX sensors remained near 160 msec. While the TD for the two paired BT-IMUs was consistently near zero.

Discussion

The results of this study are three-fold. First, accelerometer signals generated by the BT-IMU are delayed by 150-160 msec compared to the APEX device (1, 15). This lag remains consistent within a session as TD values prior to and after a 2-hour session are nearly identical. Unfortunately, the TD is not consistent between sessions and varies from one day to the next. Temporal synchronization of sensor networks has been previously addressed at length (e.g. 11, 15). For Bluetooth devices, latency in the signal (compared to other devices) can be introduced by software and hardware limitations, presence of other wireless networks, radio signal interference, and distance between devices. This delay can range from 5-300 msec (12, 13) depending on the above factors. As these conditions vary from day-to-day, it is not surprising to find variability in the TD. This day-to-day inconsistency emphasizes the need to perform a synchronization routine each day. Second, the TDs between BT-IMU units are very consistent between the two paired sensors during both controlled impacts and running. In nearly all cases, the TD was less than 1 msec. Thus, data from these multiple BT-IMU devices need minimal if any synchronization. Also, the acceleration signals from paired BT-IMU sensors show high similarity with less than 2% difference. Lastly, when the TD is accounted for, there is considerable similarity in the BT-IMU and APEX accelerometer signals. This was demonstrated through cross-correlation analysis as well as comparing peak accelerations during controlled impacts. After accounting for the time delay, it appears that the difference between devices on the order of less than 10% difference across the length of the signals.

The advantage of using cross-correlation for temporal alignment and evaluation of signal similarity is that the analysis takes into account the entirety of both acceleration signals (2,14). In short, it aligns or overlays the two signals then calculates their differences over the entire length of the data. Normalized CCF values range from -1 to 1. In this study, the normalized CCF_{max} represent the maximum Pearson-Product correlation, simplifying interpretation of the value. By comparison, peak analysis compares only two distinct points – the peak accelerations associated with controlled impacts. Thus, much of the signal is not compared and differences between other aspects of the two signals are not analyzed. For example, two signals with similar peak acceleration values might show low CCF_{max}. While high acceleration peaks may be similar, differences in lower acceleration values would decrease CCF_{max}. Thus, when comparing two signals, it is important to use a process that accounts for the entirety of the signals.

A multi-step process was used to temporally synchronize signals: 1) pre-process and filter signals, 2) adjust signals to a consistent sampling frequency using the MATLAB $< resample >$ function, 3) determine BT-IMU signal delay (TD) using cross correlation ($< xcorr >$ and $< findpeaks >$), then 4) apply the signal delay to the BT-IMU data, shifting it forward in time. This sequential procedure was done to evaluate each step of the process. However, there are additional functions provided by MATLAB which may reduce programming steps and processing time. Several temporal alignment commands are available such as $< retime >$ and $< synchronize >$ to align timestamped data with a single command. Also, once signals are resampled, one could utilize several commands align data via cross-correlation: $< finddelay >$ which uses cross correlation to return the TD value and $< alignsignals >$ determines the TD using $< finddelay >$ then applies it to align both signals in time.

In the running study, all three sensors were mounted in the same location so that each would experience the same movements. However, when used in the field, the APEX unit is mounted on the trunk and the BT-IMUs are attached to the lower leg. As a result, the APEX unit registers both right and left foot strikes during running whereas each BT-IMU sensor detect only left or right foot strike data. In addition, the accelerometer data from the APEX would be dampened during running. Thus, the three devices would be recording different sets of events. Because of this, it is not possible to directly align signals from sensors attached to different body locations. In this case, a daily alignment routine should be developed and used to determine TD values. This routine could be similar to the controlled impact approach used here, i.e., applying simultaneous impacts (accelerations) to all three sensors or applying some other simultaneous, controlled movements. By using such a procedure, all three sensors record identical events and the cross-correlation process can be applied to determine the TDs. These would then be used to temporally align trunk- and ankle-mounted sensor data (for an example, see companion paper, 18).

Practical Applications

This study demonstrates two important concepts. First, accelerometer signals originating from multiple devices can easily be temporally synchronized using cross-correlation. Second, there is considerable similarity between accelerometer signals obtained from the APEX and BT-IMU sensors. This suggests that sports scientists can compare raw data from several sensors collected during a short time frame, e.g., several hundred milliseconds. In the configuration used here, GPS, accelerometer and gyroscope data could then be used to assess gait characteristics such as spatiotemporal variables, shock attenuation and trunk vs tibial rotations. Each of these concepts could be applied to the evaluation of gait during a post-injury rehabilitation period.

Limitations

- This study was limited to straight running. Participants did not engage in any cutting or turning maneuvers.
- Only two device types were used in this study. The APEX and BT-IMU. Comparing sensors from other manufacturers may yield different results.
- The assessment of temporal alignment "drift" was limited to ~2 hours. It is possible that TD values may begin to vary beyond this time-frame.
- Resultant accelerometer signals (a_r) were analyzed. Additional work is needed to verify similarity between vertical, mediolateral and anteroposterior accelerations from the two types of sensors. Also, verification of gyroscope similarity between the devices is needed.

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