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Synchronization of wearable motion capture and EMG measurement systems

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***Abstract*— Synchronization of motion capture systems with other modalities in out-of-the-lab settings is not trivial. Various synchronization methods exist, such as using servers or transistor-transistor-logic pulses. However, not all measurement set-ups allow for such synchronization methods. Therefore, we have developed and validated an acceleration based post-measurement method to synchronize an IMU based motion capture system and an EMG measurement device. On top of the thigh IMU an additional accelerometer was placed which was connected to the analog input of the EMG device. By applying cross-correlation continuously, the similarities in the measured acceleration by the two measurement systems can be used for synchronization. We performed a validation measurement on seven able-bodied subjects and tested various correlation window sizes in hour long measurements in an out of the lab setting. It can be concluded that the developed method works for different activities when a suitable window length is chosen for cross-correlation. If no other options are available for synchronization, this correlation based method using an additional accelerometer is a viable option.**

I. INTRODUCTION

Motion analysis using optical markers is considered to be the gold standard in movement science. It enables research into the nature of musculoskeletal and neurological disorders by analyzing movement patterns. Combining motion capture with other modalities, such as electromyography (EMG), gives more insight in typical and pathological movement. These multi-modal set-ups are often used within gait laboratories. One difficulty of measuring with multiple modalities is that every system runs at different sample frequencies, which makes it difficult to synchronize data streams. Sample frequencies can range from 50 Hz for camera, to 1000Hz for EMG up to 40 kHz for audio [1]. If two devices are not synchronized, it becomes impossible to relate data of one device to the other.

One way of synchronizing two modalities is recording on one device in one software. For example Qualysis [2] and Vicon [3] offer integration of their motion capture systems with other modalities such as EMG and force plates. In this way, data were acquired by the same device, thus the same trigger clock, which gives the correct timestamps to the samples even if the samples are collected at different sample frequencies. However, it is not always possible to use all modalities recording on the same device. When using multiple devices with their own internal clocks, synchronization becomes more difficult, as the offset between two clocks will always drift over time, the so-called clock drift [4]. This can be solved using a server, for instance Lab Streaming Layer [5]. In this scenario, the data is pushed to the server (i.e. the device where the software is running on), which handles the time coding, different sampling frequencies in real-time and ensures synchronization of the different modalities [1], [6], [7], [8]. This method requires the access to the application programming interface (API) of the measurement systems. This is not always possible, especially in clinical settings [1].

Based on the aforementioned limitations, another way of synchronization could be preferred. Pulses recorded simultaneously on the different measurement devices are commonly used for synchronization purposes. Transistor-Transistor-Logic (TTL) ports enable recording of such pulses and are used in multi-modal set-ups [1], [9], [10]. If a measurement device does not allow recording of such pulses other solutions exist. Artoni *et al* proposed a fall-back method for clinical settings to synchronize EMG and EEG [1]. As no APIs or TTL ports were available on the used EMG device, no 'standard' approaches for synchronization could be used. Therefore, the authors connected a pulse generator to one of the EMG channels and to the EEG device. In this way they were able to synchronize both devices in a ten minute measurement. They also showed that the drift between the two devices behaves linearly and when not accounted for could lead to 10 ms misalignment within 60-80s. The downside of this method is that an EMG channel needs to be sacrificed to synchronize the two modalities.

The above described scenarios are all placed within the laboratory setting. A disadvantage of a lab setting is that subjects might not behave in a similar way as they would in a daily environment. Therefore, one might prefer to measure subjects in a real-life environment, such as at home. However, using multi-modal set-ups outside laboratory settings is not trivial. One might use wireless communication with a wearable computer to record all the data or use multiple wearable computers and use Lab-Streaming-Layer for example. However, this might not be feasible if APIs are not present or the weight and placement of the wearable computers or devices on a subject is an issue. Also wireless communication could induce delays into the system. TTL is an option if devices are able to use it. For instance the inertial measurement unit (IMU) based motion capture system of Technaid [11] allows third party synchronization

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using a wireless trigger system which could utilize TTL. Another commercial available full-body IMU based motion capture system is produced by Xsens [12]. They provide a synchronization station as well, which could utilize TTL. However, there is a drawback as this device cannot be used during on-body recordings outside the lab. The reason behind this is that the synchronization device is too bulky and their software is not able to use it in on-body recording-mode. Therefore, other modalities, such as EMG, cannot be synchronized during on-body recordings when no additional computer is present to record synchronization pulses. And again, if no TTL ports are available, this method cannot be used. This is a major limitation of the set-up.

Therefore, a solution has to be found for synchronization of wearable set-ups that are used outside the lab. Bannach *et al* propose an event based synchronization method with IMUs using event spotting [13]. Their algorithm consists of two parts, event spotting and using the events to synchronize audio, IMU and force sensor data streams in their network. In this way they were able to validate their method and synchronize multiple sensor streams up to five hours. This approach requires the user to perform events that can be recognized in all sensor streams, such as hand clapping. The downside of event spotting is that events need to be performed and identified. This identification could be automated, but might become difficult in long lasting measurements as other similar events might come up, which leads to inaccurate synchronization. Next to that, it could happen that events are not recorded properly and systems cannot be synchronized. Another example of a synchronized multi-modal measurement system outside a laboratory setting is described by Hasler *et al* [14]. They used multiple cameras for motion capture to investigate markerless tracking outdoors. The cameras were synchronized by measuring sound on both devices [14], [8]. Using cross-correlation between the measured sound of the cameras, they were able to time synchronize the multiple devices continuously. The principle of measuring a common signal throughout the multi-modal measurement set-up could also be used in synchronization of IMU based motion capture and other modalities. In case of IMUs and other devices this common measured signal can be acceleration. As accelerometers are relatively cheap and small, they could easily be placed on top of an IMU to measure similar acceleration. However, the question arises where these two signals would be similar enough for on-body multi-modal long-lasting recordings. In conclusion, limitations of current methods of synchronization for wearable, out of the lab set-ups are the absence of TTL, no access to APIs or the use of servers.

To address the listed limitations, we aim to develop a new continuous synchronization procedure that can easily be implemented, without the need for event spotting. To achieve this aim, this article describes the development and validation of an acceleration based synchronization of an IMU based motion capture system and a EMG measurement system which allowed recording of auxiliary analog signals.

II. MATERIALS & METHODS

A. Experimental set-up

Seven able bodied subjects (three male, four female) participated in this study. Subjects were 23 ± 2 years, 177 ± 13 cm tall and weighed 71 ± 11 kg. All subjects declared to be free of any gait impairments at the time of the measurements.

Two devices needed to be synchronized: the MVN Link suit (Xsens, Enschede, The Netherlands), and the Sessantaquattro (Bioelettronica, Turin, Italy), which were used to measure kinematics and EMG of the upper leg respectively.

The MVN Link suit consisted of eight inertial measurement units (IMUs) which were placed on the sternum, pelvis, both thighs, shanks and feet. 3D acceleration, velocity, position as well as 3D angular velocity and position were recorded per segment at a sample frequency of 240 Hz (sample time of 4.17 ms). IMU placement and calibration was performed according to Xsens guidelines [15]. The system was set to on-body recording mode, thus external synchronization was not possible.

The Sessantaquattro did not have integrated accelerometers and thus an additional accelerometer had to be used. The accelerometer ADXL337 (Analog Devices, Norwood, MA, USA) was placed on top of the Xsens IMU on the right thigh of the subject to measure similar acceleration. The accelerometer was connected to the auxiliary port of the Sessantaquattro, measuring 2D accelerations at 2000 Hz.

Signals were recorded using MVN studio v2018.2 and OT Biolab+ v1.3. Processing was done offline using Python 3.7 [16].

B. Proposed method

The proposed method consisted of cross-correlating measured acceleration by the Sessantaquatro continuously with the acceleration measured by the Xsens IMU. This meant that acceleration of the IMU and the acceleration from the additional accelerometer, measured by the Sessantaquattro were continuously compared using cross-correlation, to synchronize both systems. Cross-correlation is a measure of similarity between two functions expressed as the shift in time of one function relative to the other [17]. The maximum in the cross-correlation denotes where the two signals are most positively correlated. The location of the maximum indicates the time difference or lag τ between the two signals and is defined as:

$$\tau = \mathtt{argmax}_t (f * g)(t) \tag{1}$$

Where f and g indicate the two different signals. This property makes the cross-correlation function commonly used in pattern recognition, as it becomes possible to find similarities between a sample (or pattern) and another signal.

In this case continuous synchronization consisted of extracting windows of certain length from the acceleration measured by the Sessantaquatro and cross-correlate those with the acceleration measured by the Xsens IMU. If the signals are similar enough, clear maxima will be visible in the cross-correlation signal and the delay between the two devices can reliably determined. Especially when measuring for longer periods of time this method is suited to estimate clock drift and enables the detection of data-loss.

Because outliers can have a large influence on the estimated clock drift, it is important to detect outliers in the delay estimation. Outliers were detected based on the median and the interquartile ranges (IQRs) as described by Vinutha *et al* [18]. A data point was considered an outlier, if it lied outside the $1.5\times$IQR bounds. These outliers were removed and from the remaining data points the delay and thus the clock drift could reliably be estimated, see also Figure 3.

The gravity component needed to be removed from the acceleration measured by the Sessantaquattro, as Xsens only provides acceleration without gravity component. The gravity component was removed using a second-order zero-lag butterworth high-pass filter of 0.5 Hz. Prior to synchronization both signals were resampled to 1000Hz.

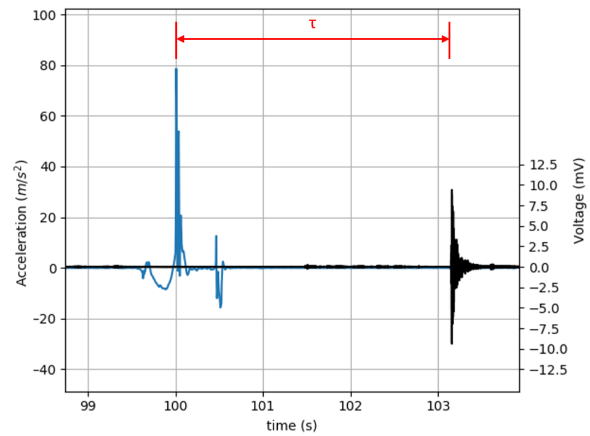

Fig. 1. Delay τ estimation using event based approach. The acceleration (blue) and the sound (black) of the kick happen simultaneous in real-life, but are shifted in their local time frame. Hence the need for synchronization.

C. Validation study

The proposed method was validated with another method of synchronization. This secondary synchronization was based on event spotting. The subject performed an event which made sound and involved acceleration, comparable to hand clapping as used by Bannach *et al* [13]. In this study this event was kicking against a cylinder.

1) Protocol: Subjects kicked the metal cylinder, stood still while the cable to the microphone was disconnected. Hereafter the subject performed movements which were used by the proposed method as described in section II-B: the subject sat down in a chair, stood up, walked approximately five meters and back and stood still again. Hereafter the cable was reconnected. Kicking and the movements were repeated three times each to get a reliable average estimate of delay between the two systems.

During the kick, acceleration was measured by foot IMU of Xsens MVN Link and the sound was recorded via the EMG channels of the Sessantaquattro, using SRS-5 speakers (Sony, Tokyo, Japan). The microphone was placed within ten centimeter from the cylinder.

2) Analysis: The moment of impact was defined as the peak acceleration in the direction of the kick measured by the foot accelerometer and the onset of the peak in sound, which happen simultaneously in real life. However, as the measurement devices were not turned on simultaneously, the event was registered at different times by different devices, with an estimated delay τ, see Figure 1.

To estimate the delay by the proposed method, windows of 10 seconds were used and applied each second during the described movements. The delay estimation of the proposed method was hereafter compared with the delay estimation of the event spotting based method.

D. Clock drift modeling

The second part of the study consisted of a long-lasting measurement. The reason for this was that two systems can become desynchronized over time although they have been synchronized before, due to clock drift [4]. Therefore, this protocol had the goal to give insight in two things. Firstly, the stability of the synchronization method, i.e. could we use the proposed method continuously for synchronization. Secondly, if we could use the proposed method to estimate the clock drift between the two used measurement systems and correct for it.

1) Protocol: One hour-long measurements were conducted in and around Roessingh Research & Development, Enschede, The Netherlands. Activities which were recorded included sitting, standing, walking on even ground, walking in confined spaces walking on uneven terrains such as grass, stair ascent/descent and ramp ascent/descent. Each activity was performed multiple times in random order outside the lab over the span of approximately one hour, while continuous recording data. Subjects first were asked to stand up from a bench, walk over grass and return. Next, the subjects walked over a parking lot towards a different building. Here subjects were asked to sit, stand up, ascent two flights of stairs, and come back down again. Hereafter, the subject was asked to ascent a different type of stairs and walk down a ramp, turn around, walk up the ramp and descent the stairs. After completing this activity, the subjects was asked to walk over different types of uneven terrain. Finally the subject was asked to walk to a different building, perform an activity to simulate confined spaces. The subject walked with small steps, forward, diagonally, backwards and sidewards. Each activity was repeated ten times, but the recording was done in one long trial. This meant that the data consisted of similar activities throughout the measurement trial.

2) Analysis: Clock drift needs to be taken into account for long lasting measurements [4]. This process is linear [4] and Artoni *et al* showed that this would influence synchronization for measurements longer than 10 minutes [1]. Therefore, the delay should be modelled as follows and is an extension of formula 1:

$$\tau(t) = a \cdot t + \tau(0) \tag{2}$$

τ is the delay between the devices at time t, which is estimated using equation 1 at various points in time. The slope of the clock drift itself is modelled by a. By estimating a, one of the systems with sampling frequency fs can be resampled to the sampling frequency of the other system (fs_{new}) to synchronize both signals. This frequency adjustment is shown below:

$$fs_{new} = \frac{1}{1-a} \cdot fs \tag{3}$$

To see the influence of clock drift, the cross-correlation based method was applied to a measurement of an hour. The data contained many repetitions of the same activity, e.g. walking. This meant that small window sizes would result in many similarities throughout the measurement and a wrong estimation of the delay. Therefore, the question arose which window length was optimal for a measurement with a longer duration. Thirteen different window lengths were tested: 10, 20, 30 seconds and 1 to 10 minutes with increments of 1 minute. Each 10 seconds of the measurement a window in the acceleration signal was extracted from the IMU and cross correlated with the acceleration measured by the accelerometer, according to equation 1. The clock drift between the two devices was estimated using equation 2.

If the proposed method was robust enough, the linear behaviour of the estimated clock drift could be seen. Xsens estimated that the internal clock of the Link system runs with a precision of 30 parts per million (ppm) [15]. Bioelettronica uses an internal clock with a precision of 50 ppm in the Sessantaquatro. In the worse case scenario, both clocks would deviate with 80 ppm from each other. We considered a synchronization attempt successful if the estimated slope would be below 1000 ppm. In this way we can automatically detect whether synchronization was successful or not.

Next to the clock drift, we monitored the clock stability as well, so-called jitter. This is defined as the standard deviation of the misalignment after adjusting for clock drift, as according to Artoni *et al* [1]. If the jitter would exceed the sampling time of the slowest modality the method would not be suited for synchronization. The limit in this case would be 4.17 ms (240 Hz).

III. RESULTS

A. Validation

Results are shown in Figure 2. Average delay difference between the event spotting based method and the cross-correlation based method was 1.3 ± 1.4 ms. The difference between the two methods falls below the intersample time of the slowest modality used in this study, namely 4.17 ms.

B. Clock drift

The delay estimations using the cross-correlation based method for the different window lengths during the hour long measurements are shown in Table I. It can be seen that the clock drift is around 24.4 ppm for each window and the jitter is between 1.2-1.7 ms. For short time windows, i.e. below 1 minute, the method failed. Between 1 and 3 minutes the method was able to synchronize the devices for most subjects and for windows longer than 3 minutes the method succeeded for each subject. The histogram of the jitter after compensating for the clock drift shows a normal distribution with a standard deviation of around 1.6 ms, see Figure 2. In Figure 3 can be seen that the clock shift behaved linearly as expected.

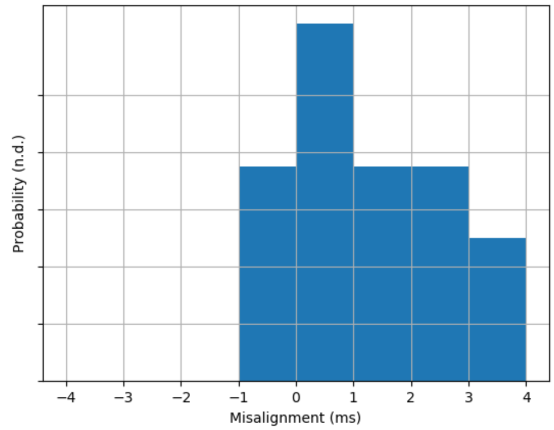

Fig. 2. Differences in estimated delay of the event spotting based method and the cross-correlation based method.

TABLE I
RESULTS OF SYNCHRONIZATION USING VARIOUS WINDOW SIZES FOR CROSS-CORRELATION. IT SHOWS THE SUCCESS RATE OF THE METHOD, THE ESTIMATED CLOCK DRIFT IN PARTS PER MILLION (PPM) AND THE ESTIMATED JITTER.

Window	Success	Clock drift (ppm)	Jitter (ms)
10 s	0/7	-	-
20 s	0/7	-	-
30 s	0/7	-	-
1 min	5/7	24.4	1.6
2 min	6/7	24.4	1.4
3 min	6/7	24.3	1.2
4 min	7/7	24.5	1.3
5 min	7/7	24.5	1.3
6 min	7/7	24.5	1.4
7 min	7/7	24.4	1.5
8 min	7/7	24.4	1.5
9 min	7/7	24.4	1.6
10 min	7/7	24.4	1.7

IV. DISCUSSION

The goal of this study was to develop a synchronization method that could be used for wearable modalities when other synchronization methods are not feasible, e.g. when measuring outside laboratory settings. The described method uses cross-correlation to determine the delay and clock drift between two modalities and can be used continuously.

Delay estimation difference between the event spotting based method and the cross-correlation based method fall within the sample interval time of the modality with the lowest sample frequency. The sample interval time of the Xsens IMU was 4.17 ms, whereas the estimated delay was within 4 ms between the two methods. Results of the

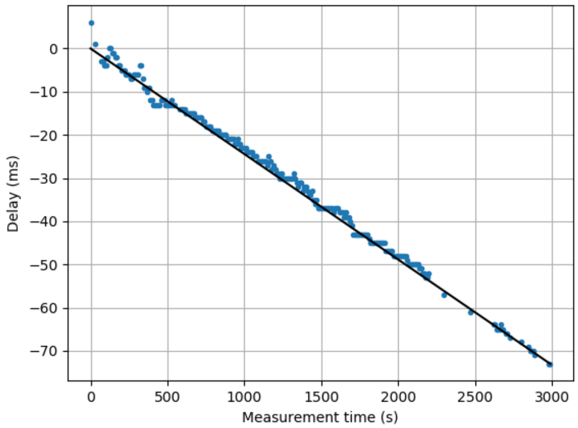

Fig. 3. Delay over time (blue) using 1 minute windows, estimated each 10 seconds by using cross-correlation. The slope (black) was estimated after outlier detection and this represents the clock drift. Around 2400 seconds a gap could be seen where outliers were removed. In this section a subject walked from one location to another, thus the extracted windows looked very similar to other walking activities and the correlation method failed.

hour-long measurement show that the jitter is also below this sample interval time, which shows the stability of the proposed method. Thus the resolution of the cross-correlation based method is adequate to be used for synchronization of the two measurement systems.

The cross-correlation based method was applied to different activities. During the validation study these were walking and sitting and the delay could reliably be estimated between the two devices. The hour long measurements contained multiple activities, from walking to stair climbing to sitting. These different activities did not influence the delay estimation and thus the proposed method can be expected to be reliable in different types of activities. However, two things are important to note: First, to perform synchronization, acceleration needs to be measured. If no acceleration is measured, no accurate delay can be estimated using cross-correlation. When placing this set-up on other body parts acceleration needs to be measured by both accelerometers to accurately estimate delay. Second, the activity performed has to be unique. This means that if many repetitions of the same movement are conducted, short time windows would result in wrongly estimated delays. If the previous step is very similar to the next step, there is not much variability in the signal. This means that an extracted window will also look very similar to other windows and thus is not unique. These non-unique windows result in maxima in the cross-correlation at various locations which will result in wrong estimation of delay. This can be seen in the window lengths below 1 minute in Table I, which resulted in all fails when trying to estimate the shift in delay. Using 1-3 minute windows resulted in a success most of the time, although some still failed. Synchronization for all subjects was only achieved using window lengths of 4 minutes or larger in this measurement set-up. Longer time windows make the extracted window more unique and thus suitable for synchronization. When measuring activities which are not very similar, such as walking on uneven terrains (i.e. the previous step is different than the next), one could expect that shorter window lengths would suffice. For treadmill walking, longer window lengths might be necessary as steps are very similar to each other, thus resulting in non-unique windows at small window lengths. However, mostly when performing experiments on a treadmill, this is within a laboratory setting with other possible ways of synchronization. Another solution would be to choose situations during the measurement where the movements are more unique, e.g. during free walking or turning or letting the subject perform an odd movement and then only using windows during those unique movements to synchronize. This actually becomes similar to event spotting [13] and one needs to consider which approach would suit best to their measurement protocol. In this study we did not investigate this approach as we can afford longer windows for synchronization, as our measurements were up to an hour and we did not want to perform certain events and event spotting for synchronization.

In Table I shows that the clock drift was around 24.4 ppm. This is typical for the measurement set-up that was used. If using a different measurement device, the internal clock could be slightly different which results in a different clock drift. Other measurement set-ups will therefore have other clock drifts. It is important to compensate for this drift or else relations between two measured entities will no longer be valid. For instance, when synchronizing EMG and kinematics, one would need a synchronization resolution below 100 ms at all times. Wentink *et al* showed that the onset of EMG can be measured 138 ms in advance of movement [19]. After an hour of measurement, this relation would no longer be valid, as the delay between two systems has shifted. In this measurement set-up the clock drift at 24.4 ppm would result in a delay of approximate 88 ms after one hour of measurement. These time delays are also critical in other situations, for instance when relating EEG and EMG data, as shown by Artoni *et al* [1]. Klein showed that poor synchronization can influence classification results negatively as well and stresses the importance of synchronization [4]. It is therefore important to detect this clock drift and correct for it, as we showed in this paper.

Placement of the accelerometer on other body segments was not investigated in this research, however, it can be expected that the method will perform equally well. This is because the acceleration measured during movements is similar enough to be used for synchronization if two sensors are placed on top of each other. One could assume that this method works in a patient population as well. As long as movement occurs and thus acceleration can be measured by two different devices, this method should be applicable, although one might need to use a different sensor location than used in this set-up if certain movements cannot be made. Another assumption that was made was that the measured sound is instantaneous. This is not completely true, as sound travels with around 3 ms per meter. Therefore, the microphone had to be placed close to the metal cylinder. As the distance from the microphone to the cylinder was around ten centimeter, the average delay induced by the speed of sound was 0.3 ms, thus negligible. Outlier detection was put in place to ensure outliers would not influence the clock drift estimation. Without this detection the method would be less reliable. This is because the data that needs to be synchronized contains many repetitions, thus wrongly estimated delays can occur. The subject population is small, however, looking at the distribution of jitter in Figure 3 for window size of 1 minute, the standard deviation is still below 4.17 ms. This is also seen during the validation study with maximal differences of 4ms in Figure 2. Thus it can be assumed that this method works equally well for a larger subject population.

The synchronization method described in this article is applicable in situations where there is not other possibility of synchronization or other methods are less reliable. In cases where Lab-Streaming-Layer [5] or measuring with the same device could be utilized, that method has preference. When falling back to other methods such as using TTL pulses the proposed method could be superior. The reason for this is that using a TTL pulse only at the start of the measurement might be insufficient for longer during measurements as the shift in delay between the two systems could be up to 80 ppm or 288 ms per hour as described before, or even larger depending on the set-up used. As mentioned before, it is important to compensate for this clock drift. Therefore, continuous synchronization, or at least a re-synchronization would be required and the proposed cross-correlation based method could be applied. However, using additional TTL pulses [1], [10], this problem can also be circumvented.

There is another scenario where continuous synchronization is preferred over the use of TTL pulses. In case of using wireless systems data loss could occur. If the data loss is not compensated or unknown, data between two TTL pulses becomes impossible to synchronize. However, using continuous synchronization, one is able to locate the exact moment where data loss has occurred, one could determine the duration of the data loss and is able to compensate for it. Thus in the case of using a system where data loss could occur continuous synchronization is superior over using TTL pulses.

The advantage of the proposed method over the synchronization method proposed by Artoni *et al* [1] is that no additional pulse generator is required, as the proposed method in this study uses the nature of the measured signal. The only downside is that an additional accelerometer is required, although the cost of the used accelerometer (ADXL337) is under ten US dollar. If no auxiliary ports are available in the measurement system, the accelerometer could be recorded in a EEG/EMG channel, which was proposed by Artoni *et al* [1].

V. Conclusions

The goal of the study was to develop and validate a method which can be used for synchronizing wearable modalities outside a laboratory setting using acceleration cross-correlation. The cross-correlation based method showed similar delay estimations as an event spotting based synchronization method. The proposed method was applied to hour long measurements and from the results can be concluded that the proposed method is stable with jitter below the 4.17ms sample time. Next to that, we are able to estimate the clock drift and correct for it. These results show that the described method is suitable to synchronize IMU based motion capture systems and other modalities, such as EMG measurement systems.

References

[1] F. Artoni, A. Barsotti, E. Guanziroli, S. Micera, A. Landi, and F. Molteni, "Effective synchronization of EEG and EMG for mobile brain/body imaging in clinical settings," *Frontiers in Human Neuroscience*, vol. 11, no. January, pp. 1–9, 2018.

[2] Qualisys, "Motion Capture Systems." www.qualisys.com.

[3] Vicon, "Award Winning Motion Capture Systems." www.vicon.com.

[4] B. N. Klein, *On the importance of time synchronization for context aware applications*. Kassel University Press GmbH, 2012.

[5] Swartz Center for Computational Neuroscience, "LabStreamingLayer." github.com/sccn/labstreaminglayer.

[6] A. Ojeda, N. Bigdely-Shamlo, and S. Makeig, "MoBILAB: An open source toolbox for analysis and visualization of mobile brain/body imaging data," *Frontiers in Human Neuroscience*, vol. 8, no. MAR, pp. 1–9, 2014.

[7] J. Wagner, R. Martinez-Cancino, A. Delorme, S. Makeig, T. Solis-Escalante, C. Neuper, and G. Mueller-Putz, "High-density EEG mobile brain/body imaging data recorded during a challenging auditory gait pacing task," *Scientific data*, vol. 6, no. 1, p. 211, 2019.

[8] W. T. J. L. Pouw, J. P. Trujillo, and J. A. Dixon, "The Quantification of gesture-speech synchrony: a tutorial and validation of multi-modal data acquisition using device-based and video-based motion tracking," *Behavior research methods*, 2018.

[9] A. Worley, L. Fabrizi, S. Boyd, and R. Slater, "Multi-modal pain measurements in infants," *Journal of Neuroscience Methods*, vol. 205, no. 2, pp. 252–257, 2012.

[10] C. Maidhof, T. Kästner, and T. Makkonen, "Combining EEG, MIDI, and motion capture techniques for investigating musical performance," *Behavior Research Methods*, vol. 46, no. 1, pp. 185–195, 2014.

[11] Technaid, "Leading Motion - Analysis Motion Capture." www.technaid.com.

[12] D. Roetenberg, H. Luinge, and P. Slycke, "Xsens MVN: Full 6DOF human motion tracking using miniature inertial sensors," *Xsens Motion Technol. BV Tech Rep*, vol. 3, pp. 1–9, 2013.

[13] D. Bannach, O. Amft, and P. Lukowicz, "Automatic event-based synchronization of multimodal data streams from wearable and ambient sensors," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 5741 LNCS, pp. 135–148, Springer, Berlin, Heidelberg, 2009.

[14] N. Hasler, B. Rosenhahn, T. Thormählen, M. Wand, J. Gall, and H. P. Seidel, "Markerless motion capture with unsynchronized moving cameras," in *2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops 2009*, vol. 2009 IEEE, pp. 224–231, IEEE, 6 2009.

[15] Xsens, "Xsens MVN Analyze - Products." xsens.com/products/xsens-mvn-analyze/.

[16] Python Software Foundation, "Python, version 3," 2009.

[17] S. Haykin and M. Moher, *An Introduction to Analog and Digital Communications*. Wiley Textbooks, 2012.

[18] H. P. Vinutha, B. Poornima, and B. M. Sagar, "Detection of Outliers Using Interquartile Range Technique from Intrusion Dataset," pp. 511–518, Springer, Singapore, 2018.

[19] E. C. Wentink, V. G. Schut, E. C. Prinsen, J. S. Rietman, and P. H. Veltink, "Detection of the onset of gait initiation using kinematic sensors and EMG in transfemoral amputees," *Gait and Posture*, vol. 39, no. 1, pp. 391–396, 2014.