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An Automatic Foot and Shank IMU Synchronization Algorithm: Proof-of-concept*

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***Abstract*— When using wearable sensors for measurement and analysis of human performance, it is often necessary to integrate and synchronise data from separate sensor systems. This paper describes a synchronization technique between IMUs attached to the shanks and insoles attached at the feet and aims to solve the need to compute the ankle joint angle, which relies on synchronized sensor data. This will additionally enable concurrent analysis using gait kinematic and kinetic features. A proof-of-concept of the algorithm, which relies on cross-correlation of gyroscope sensor data from the shank and foot, to align the sensor systems is demonstrated. The algorithm output is validated against those signals synchronized using manually annotated heel-strike and toe-off ground-truth signal landmarks, identified in both the shank and feet signals using previously published definitions. Results demonstrate that the developed algorithm is capable of synchronizing both sensor systems, based on IMU data from both healthy participants and participants suffering from knee osteoarthritis, with a mean lag time bias of 25.56ms when compared to the ground truth. A proof-of-concept of technique to synchronise IMUs attached to the shanks and insoles attached at the feet is demonstrated and offers an alternative approach to sensor system synchronisation.**

I. Introduction

Wireless body-worn inertial measurement units (IMU) are regularly used for the measurement of human biomechanics, such as gait analysis and joint angle measurement [1], [2]. In such analysis, for optimum measurement performance, sensors are attached to the lower extremity, on the segments of interest (e.g. feet, shank and/or thigh) for gait analysis and join angle measurement.

To enable ongoing studies in the field, we have developed a biomechanical sensing platform (BSP) which consists of 5 wireless body-worn IMUs, foot pressure insole units (ISUs) and an Android based application. The BSP is suitable for the measurement of lower extremity gait biomechanics. The BSP combines two separately developed sensor systems. A set of 5 Physilog IMUs (GaitUp, Lausanne, Switzerland)[1] and a set of foot pressure insoles with integrated IMUs, from Moticon (Moticon ReGo AG, Munich, Germany)[2], illustrated in Figure 1. Data from the two sensor systems are transmitted via Bluetooth™ to the BSP app, which is a custom designed Android application.

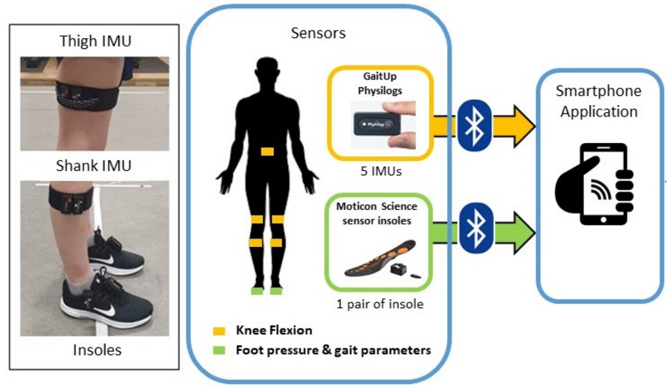

Fig. 1. The BSP consisting of five GaitUp Physilog6 IMUs, which consist of tri-axial acceleroemter and gyroscope sensors, samples at 128Hz. As well as two Moticon insole units, which contain 16 plantar pressure sensors and tri-axial accelerometer and gysroscope sensors, sampled at 100Hz

With this combination of inertial sensors and foot pressure insoles, distributed across the lower extremity, the BSP is capable of measuring spatiotemporal gait parameters and lower limb kinetics and kinematics [1], [3]. However, a major practical challenge, when combining separately developed wireless sensor systems, is how to temporally synchronize data streams between these separate sensor systems. This is especially critical if algorithms rely on sensor fusion (e.g., joint angle computation or multi-segment activity classifiers) thus requiring that sensor data are optimally synchronized to avoid large misalignment which can cause computed features to be unreliable or inaccurate.

Extensive effort has been devoted to efficient clock synchronization methods for wireless sensor networks [4], [5]. These approaches often rely on elaborate messaging transfer and time distribution protocols between the network nodes. However, application and implementation of such approaches could be delayed or unfeasible for one, or a combination of several different reasons. These include, but are not limited to, different types of wireless network communication protocols, different hardware radio chipsets, different SDKs and/or different firmware. Non-trivial software and/or hardware solutions are required to overcome these scenarios.

This work does not aim to replace wireless sensor network synchronization protocols, but offers an alternative approach where this type of synchronization solution is not possible, or in anticipation of such a solution being implemented.

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[1]https://gaitup.com/
[2]https://moticon.com/

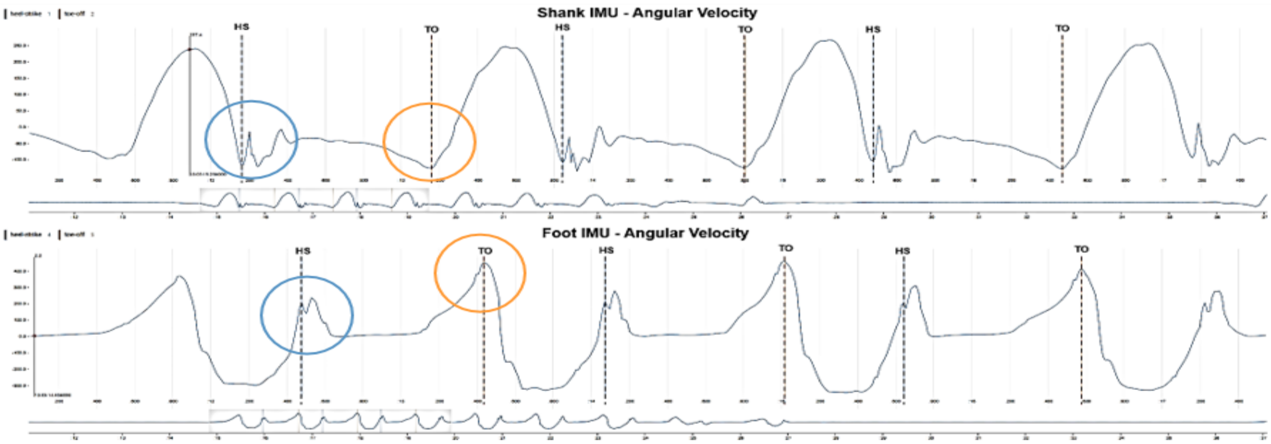

Fig. 2. Example illustrating the annotation tool. The heel-strike and toe-off events were annotated for the first three steps of the gait bout.

Common practice for such an alternative approach involves event-based synchronisation techniques [6]. The individual sensor nodes are synchronized through an event-based approach, either through manually generating and detecting a synchronization handshake [7], [8] or as a feature of the movement being measured [9] in raw inertial sensor signals.

The aim of this study is to develop and evaluate an event-based synchronization algorithm that is applicable during gait bout recording, taking advantage of the inherent gait features.

The structure of this paper is organized as follows: Section II describes the experimental set-up, the approach to generating the ground truth data to evaluate the algorithm performance and synchronization algorithm is described. Section III presented the results of the validation experiment. Section IV discusses the experiments performance and derives the application area and limitations of the approach. Finally Section V summarizes the key points of the paper.

II. Methods

A total of four participants (two healthy participants and two participants with knee osteoarthritis) were recruited. The seven sensors, as part of the BSP, were attached to each participant, as depicted in Fig. 1. Each participant was recorded performing a series of seven separate walking bouts, which included six 6m walking bouts and one 2-minute walking bout. Data from the sensors were streamed wirelessly via Bluetooth™ to the Android based application. The IMU data were resampled to 100Hz and two raters manually annotated the first three heel-strike and toe-off events, in each foot and shank sensor data, for each walking bout, to create a ground-truth reference data-set. The synchronisation algorithm, to automatically align the sensors systems, was then applied and resulting output evaluated. All analysis was performed using the R software, version 3.4.2.

A. Ground truth

The ground truth data-set of heel-strike and toe-off signal landmarks were annotated by two independent raters using the open source software package label-studio[3]. The following definition for identifying the heel-strike and toe-off landmarks, in the raw inertial sensor data, are supported with definitions and descriptions sourced from existing literature.

1) Heel-strike and toe-off signal landmark definitions: The foot-flat phase of the gait cycle as measured by a pitch gyroscope sensor, attached to the foot or the shank, is characterized by low, or near zero, sagittal plane angular velocity due to the quasi-static state of the foot and shank. Between these foot-flat states, during a gait bout, the phases and events including the swing phase, toe-off and heel-strike events occur. These are characterized by a large amplitude wave peak flanked by two wave peaks in the opposite direction. The peak of the central singular wave represents the maximum swing-phase angular velocity. This central swing-phase wave is flanked on either side by wave in the opposite direction. The preceding wave peak was used to identify the toe-off event and the succeeding wave peak was used to identify the heel-strike event, for both the foot [10], [11] and the shank [12].

B. Synchronization Algorithm

The synchronization algorithm between the shank and the foot consists of three phases.

1) Gait Bout Detection: Gait bouts were identified through thresholding of the standard-deviation of the vector-magnitude of the tri-axial accelerometer signals, using a 99% overlapping rolling window of 1-second, the signal was then rounded to 1 place of decimals. Gait bouts were detected if this signal exceeded a threshold of 0.1g.

2) Cross-correlation: The maximum cross-correlation between the foot and shank pitch angular velocity signals, during the identified gait bouts, were used to identify the offset time lag between both sensors signals. This was achieved using the ccf (cross-correlation) function.

3) Aligning the raw data: Apply the lag identified, from the maximum cross-correlation, to offset the timestamp of

[3] `https://labelstud.io/`

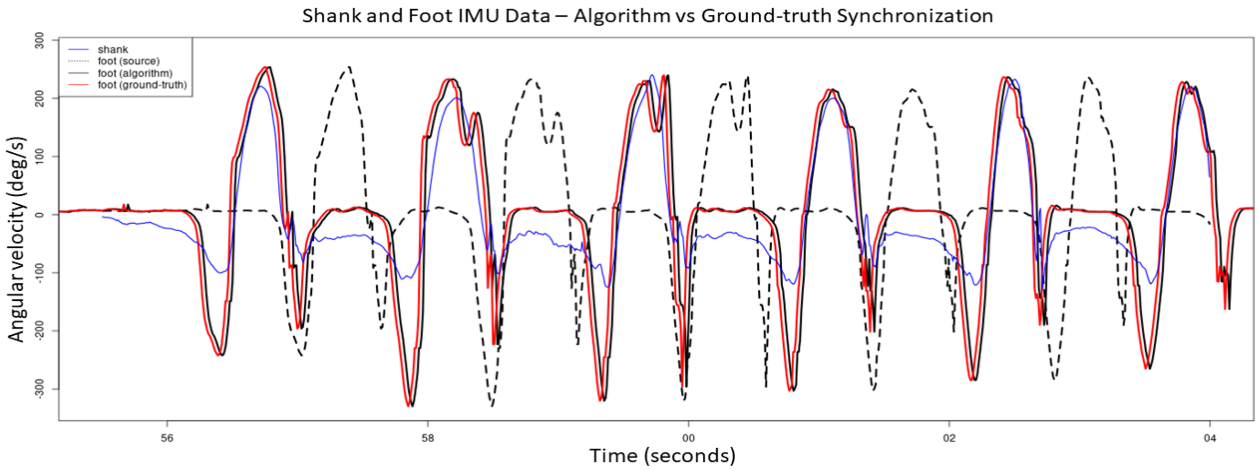

Fig. 3. Example showing the manually vs automatically synchronized shank and foot IMU sensor signals. The foot (source) signal was shifted, based on the algorithm generated lag, to align with the shank signal. The foot (algorithm) signal is compared to the foot (ground truth) signal.

one of the sensors systems to align with the nominated reference system.

C. Statistical Analysis

Pearson's correlation coefficients (ρ) were used to assess the level of agreement between both raters. The Pearson's correlation coefficient ranges from -1 to 1, with the extreme values of -1 and 1 indicating a perfectly linear relationship. Values of >0.9 are considered a very high positive correlation [13]. Correlation strengths were classified as poor (ρ<0.5), moderate (ρ=0.5 to 0.75), good (ρ=0.75 to 0.9) and excellent agreement (ρ>0.9) [14]. In addition, linear regression, with the algorithm output as the dependant variable, and the mean of the annotators (ground-truth) as the independent variable, was performed.

III. Results

A total of 28 walking bouts were recorded, from the four participants. Each of the two raters annotated a total of 672 events. These include annotations, for three heel-strike and three toe-off events, from the shank and foot sensors, from both left and right sides. Thus 24 annotated events for each recorded walking bout. Annotations from the shank and foot signals were used to compute the lag times between the two data streams, producing 336 lag times. For instance, the time difference (*td*) from the heel-strike (*hs*) from shank and the foot signals derive the offset between the two sensor data streams, i.e., $td_{hs} = hs_{shank} - hs_{foot}$. Heel-strike and toe-off events labelled, by both raters, produced excellent agreement (ρ>0.9) for the heel-strike and toe-off events separately and combined, Table I. A Pearson's correlation of ρ=0.9804, was observed between both rater's annotations, indicating a very high positive correlation, Fig. 4.

A residual standard error of 30.92 on 334 degrees of freedom with multiple R^2 of 0.8945, which implies that 89.45% of the variability of the dependent variable has been accounted for. Based on a linear regression comparing the algorithm lag against the annotator ground truth (annotator

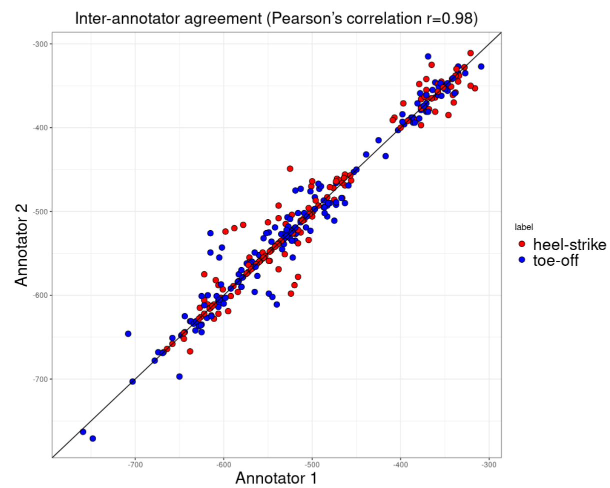

Fig. 4. Inter-annotator agreement - Pearson's correlation

TABLE I
INTER-RATER AGREEMENT

Event	ρ	(lb,	ub)	p	quantity
Heel-strike	0.978	0.971	0.984	<0.001	168
Toe-off	0.982	0.976	0.987	<0.001	168
All	0.98	0.976	0.984	<0.001	336

mean), Fig 5, we see an average bias of 25.59ms, the difference between the independent variable at its mean value (-506ms) and the output predicted by the linear regression (-481ms), Table II. Indicating that the algorithm underestimates the lag by a mean of 25.59ms when compare to the annotator ground-truth mean.

IV. Discussion

In this work we propose a novel procedure for event-based synchronisation during gait, for IMUs attached to the shanks and feet. The concept for the algorithm relies on cross-correlation of the pitch gyroscope signals from the feet and

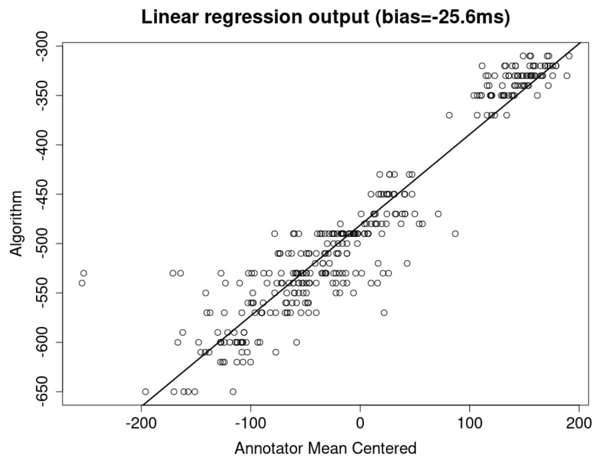

Fig. 5. Linear regression model output. The x-axis shows the average of the annotator mean centered at the grand average (-506ms)

TABLE II
LINEAR REGRESSION COEFFICIENTS

	Estimate	Std. Error	t-value	p-value
(Intercept)	-481.25	1.686	-285.29	<0.0001
Centered	0.918	0.017	53.21	<0.0001

shank sensors to synchronize the sensor data and is a novel approach that does not reply on an independently performed handshake movement or choreographed movement to be integrated as part of the protocol, but simply on the knowledge that gait data are harvested. Additionally, this approach is device and hardware agnostic and does not rely on the communication and computational hardware peripherals, or software implemented, surrounding the accelerometer and gyroscope sensors. This developed algorithm simply replies on the harvested gait data to achieve sensor synchronisation.

To evaluate the developed algorithm, we compared the algorithm results to ground truth synchronized signals, produced through identifying heel-strike and toe-off event in the raw gyroscope signals. The heel-strike and toe-off events were identified using existing definitions from literature, of the signal landmarks, for pitch gyroscope signal harvested from the foot and shank.

This technique could applied to walking bouts of different lengths and durations commonly used in clinical trial, for example, the short walk test, the 25 foot walk test, the 6 meter walk test, the 2 minute walk test [15], 6 minute walk test, time-up-and-go test, 5 U-turn test [16]. This current technique examines 3 strides as part of the gait recording and is used here to account for the time lag between the two sensors systems. However, this technique could be also applied to compensate for the relative linear time drift between the two systems. This was not applied here due to the relatively short nature of the recordings ($<$2 minutes). Future work will examine the application of this approach for offset and relative signal drift compensation of recordings of extended durations.

V. Conclusion

We conclude that the developed algorithm demonstrates the proof-of-concept of synchronizing both sensor systems, based on IMU data from shank and feet mounted sensors, in both healthy participants and participants suffering from knee osteoarthritis, with a mean lag time bias of 25.56ms when compared to the ground truth. Future work with a larger subject cohort and walking bout data-set, will establish the robustness of the algorithm and we expect that this will lead to further improvements of this synchronization approach.

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References

[1] M. O'Reilly, B. Caulfield, T. Ward, W. Johnston, and C. Doherty, "Wearable inertial sensor systems for lower limb exercise detection and evaluation: A systematic review," *Sports Medicine*, vol. 48, 2018.

[2] I. Weygers, M. Kok, M. Konings, H. Hallez, H. De Vroey, and K. Claeys, "Inertial sensor-based lower limb joint kinematics: A methodological systematic review," *Sensors*, p. 673, 2020.

[3] S. Subramaniam, S. Majumder, A. I. Faisal, and M. J. Deen, "Insole-based systems for health monitoring: Current solutions and research challenges," *Sensors*, vol. 22, no. 2, 2022.

[4] F. Asgarian and K. Najafi, "Time synchronization in a network of bluetooth low energy beacons," *Proceedings of the SIGCOMM*, 2017.

[5] M. Maróti, B. Kusy, G. Simon, and A. Lédeczi, "The flooding time synchronization protocol," in *Proceedings of the 2nd International Conference on Embedded Networked Sensor Systems*, ser. SenSys '04. Association for Computing Machinery, 2004, p. 39–49.

[6] D. Bannach, O. Amft, and P. Lukowicz, "Automatic event-based synchronization of multimodal data streams from wearable and ambient sensors," in *Smart Sensing and Context*, P. Barnaghi, K. Moessner, M. Presser, and S. Meissner, Eds. Springer Berlin Heidelberg, 2009.

[7] A. K. Bourke, E. A. F. Ihlen, R. Bergquist, P. B. Wik, B. Vereijken, and J. L. Helbostad, "A physical activity reference data-set recorded from older adults using body-worn inertial sensors and video technology—the adapt study data-set," *Sensors*, vol. 17, no. 3, 2017.

[8] S. Paraschiakos, R. Cachucho, M. Moed, D. van Heemst, S. Mooijaart, E. P. Slagboom, A. Knobbe, and M. Beekman, "Activity recognition using wearable sensors for tracking the elderly," *User Modeling and User-Adapted Interaction*, vol. 30, no. 3, pp. 567–605, 2020.

[9] T. Rietveld, R. J. Vegter, R. M. van der Slikke, A. E. Hoekstra, L. H. van der Woude, and S. De Groot, "Wheelchair mobility performance of elite wheelchair tennis players during four field tests: Inter-trial reliability and construct validity," *PLoS One*, 2019.

[10] B. Mariani, H. Rouhani, X. Crevoisier, and K. Aminian, "Quantitative estimation of foot-flat and stance phase of gait using foot-worn inertial sensors," *Gait & posture*, vol. 37, no. 2, pp. 229–234, 2013.

[11] H. Zhao, S. Qiu, Z. Wang, N. Yang, J. Li, and J. Wang, "Applications of mems gyroscope for human gait analysis," in *Gyroscopes-Principles and Applications*. IntechOpen, 2019.

[12] H. T. T. Vu, D. Dong, H.-L. Cao, T. Verstraten, D. Lefeber, B. Vanderborght, and J. Geeroms, "A review of gait phase detection algorithms for lower limb prostheses," *Sensors*, 2020.

[13] M. Mukaka, "Statistics corner: a guide to appropriate use of correlation in medical research," *Malawi Medical Journal*, pp. 69–71, 2012.

[14] L. G. Portney, M. P. Watkins *et al.*, *Foundations of clinical research: applications to practice*. Pearson/Prentice Hall Upper Saddle River, NJ, 2009, vol. 892.

[15] A. K. Bourke, A. Scotland, F. Lipsmeier, C. Gossens, and M. Lindemann, "Gait characteristics harvested during a smartphone-based self-administered 2-minute walk test in people with multiple sclerosis: test-retest reliability and minimum detectable change," *Sensors*, 2020.

[16] W.-Y. Cheng, A. K. Bourke, F. Lipsmeier, C. Bernasconi, S. Belachew, C. Gossens, J. S. Graves, X. Montalban, and M. Lindemann, "U-turn speed is a valid and reliable smartphone-based measure of multiple sclerosis-related gait and balance impairment," *Gait & Posture*, 2021.