Signal Processing Requirements for Step Detection Using Wrist-worn IMU

L.E. Díez* A. Bahillo* A.D. Masegosa* A. Perallos* L. Azpilicueta†
F. Falcone† J.J. Astrain‡ J. Villadangos‡

Abstract — **This paper studies how the accuracy of the step detection algorithm of a pedestrian dead-reckoning (PDR) system is affected by the sampling frequency and the filtering of the data gathered from a wrist-worn inertial measurement unit (IMU). On the one hand, results show that sensors sampling rate can be reduced and a similar accuracy can still be obtained, what it is very interesting for energy saving purposes. However, a low sampling frequency requires a finer tuning of the algorithm's parameters. On the other hand, the application of a filter to the data gathered from the sensors is always recommended, in order to get some performance improvement. Different types of filters can be used in function of the value of the sampling frequency.**

1 INTRODUCTION

Context-aware systems and applications usually obtain the user's position from Global Navigation Satellite Systems (GNSS), as the GPS. However, these technologies perform poorly in environments in which GNSS signals get severely degraded, or even blocked, due to multipath and attenuation losses [1], such as in "urban canyons" or inside buildings, places in which people spend the most part of the day.

Dead-Reckoning is a positioning technique based on updating a known initial position using the estimated speed and heading over time. Its adaptation to the characteristics of people's walking is often called pedestrian dead-reckoning (PDR). Thanks to the MEMS technology (Microelectromechanical systems), it is possible to build small and cheap sensors, called inertial measurement units (IMU), that contain several accelerometers, gyroscopes and, sometimes, magnetometers [2], and place them on people in order to detect their movements and implement the PDR technique. A remarkable advantage of this option is that no additional infrastructure is needed to be installed, so it is being considered as a promising solution for obtaining seamless positioning of pedestrians in scenarios where GNSS systems may get degraded.

There are two ways to implement the PDR technique [3]: applying a strapdown inertial navigation system (INS) mechanization [4] in which position is obtained by integrating accelerometer and gyroscope readings; or integrating the user's step lengths and heading angles at each detected step. For the first implementation, good results are obtained with foot-mounted IMU thanks to the possibility of introducing Zero-Velocity-Update (ZUPT) pseudo-measurements, what reduces the error drift of the inertial sensors [5]. However, this location of the sensor can be uncomfortable for the user. Using the second implementation, it has been studied to take advantage of the IMUs that all current smartphones already include. However, this option becomes complex to process due to the unconstrained location and orientation of the phone with respect to the user [6]. A wrist-worn IMU offers a trade-off: a fixed location on the body but more convenient for the user than the foot-mounted IMU. Moreover, the recent availability of smartwatches and smartbands opens up an opportunity to research this option.

The literature about PDR-based systems usually focuses on describing the detection and estimation algorithms, providing few details about how the configuration of the sensors affect their performance. In this paper, the authors pay special attention to how a wrist-worn IMU's sampling frequency and the filtering of its signals affect the accuracy of the step detection algorithm of a PDR positioning system. The objective of this study is to understand better how the step detection algorithm really works, in order to maximize its performance.

The structure of the paper is as follows: Section 2 describes related works in the field. Methodology and experimental results are described in section 3 and 4. Finally, conclusions are drawn in section 5.

2 RELATED WORK

There already exists a lot of sport watches that compute the travelled distance by counting steps

*Deusto Institute of Technology (DeustoTech), University of Deusto, Bilbao, Spain, e-mail:{luis.enrique.diez, alfonso.bahillo, ad.masegosa, perallos}@deusto.es.

†Electrical and Electronic Engineering Department, Universidad Pública de Navarra, Pamplona, Spain, e-mail:{leyre.azpilicueta, francisco.falcone}@unavarra.es.

‡Mathematics and Computer Engineering Department, Universidad Pública de Navarra, Pamplona, Spain, e-mail:{josej.astrain, jesusv}@unavarra.es.

and assuming a fixed step length. This can be enough to monitor sport activity but not for accurate positioning. To the best knowledge of the authors, only two papers try to perform position estimation from wrist-worn IMU.

In [7] they only described the PDR's step length estimation model, proposing a non-linear 2^{nd} order polynomial model that uses either fixed parameters or estimated parameters obtained by fusing GPS measures in a Kalman filter.

In [8] they described a complete PDR system: their step detection algorithm is based on the crossings of the acceleration magnitude over a dynamically updated threshold, plus some validations on temporal durations, magnitude peaks and signal periodicity; for the step length estimation, they proposed a linear polynomial model of the step frequency and acceleration variance; and for the heading estimation, they took advantage of the periodicity of the acceleration during walking to make the assumption that the offset between the IMU heading and the pedestrian will always be constant whenever the magnitude of the acceleration crosses the gravity. They worked with a 100 Hz sampling frequency and a low-pass filter was applied only for the heading estimation, no for the step detection.

3 METHODOLOGY

Firstly, the step detection algorithm described in [8] was implemented and, subsequently, the methodology followed in this paper consisted in processing several datasets, obtained from real walks, and checking the variations of the step detection algorithm's accuracy when the data's sampling frequency is modified and a filter is applied. Additionally, as the values of the algorithm's parameters are not mentioned in [8], different ranges of them were used with the objective of finding the best possible configuration.

3.1 Data collection

Figure 1 corresponds to the system used to collect real data. It was described in [9] and it is based on the 9DOF Razor IMU, provided by SparkFun Electronics.

Data collection was performed by an only subject, wearing the aforementioned IMU on his left wrist and a smartphone for data registering.

The subject took straight-line walks of 30 steps at different paces, covering the usual range of walking step frequency: from 1.5 Hz to 2.1 Hz, with increments of 0.1 Hz. A metronome was used as a pace reference to the subject.

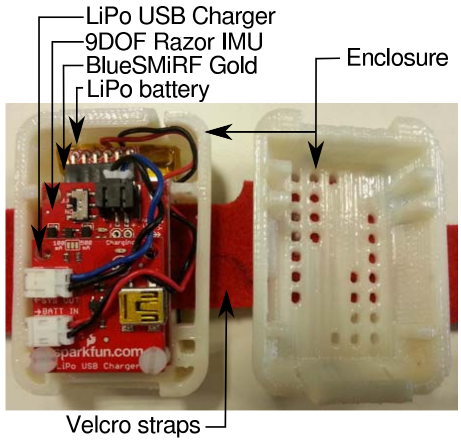

Figure 1: Low-cost Bluetooth IMU.

For every different step frequency, 5 walks were taken. Therefore, 35 different registered walks were available to be processed.

3.2 Step detection algorithm parametrization

As mentioned before, no recommended values were indicated in [8] for the algorithm's parameters. Table 1 collects the ranges of empirically obtained values that were considered in this study.

Parameter	Range of Values
Min step duration	$[0.25\,s, 0.333\,s]$
Max step duration	$[0.833\,s, 1.667\,s]$
Min peak-to-threshold	$[0.5\,m/s^2, 1.5\,m/s^2]$
Max peak-to-threshold	$[12\,m/s^2, 16\,m/s^2]$
Sliding window size	$5\,s, 6\,s, 6.5\,s, 7\,s$
Autocorrelation threshold	0.8

Table 1: Step detection algorithm's parametrization.

3.3 Sampling frequency and filtering

As the datasets were collected with the IMU's sampling frequency set to 100 Hz, in order to obtain different sampling rates, downsampling was applied on the collected data. Ignoring the right samples, the following sampling rates were obtained: 100 Hz, 50 Hz, 25 Hz, 20 Hz, 10 Hz and 5 Hz.

Regarding the signal filtering, these are the different filters that were tested:

- Moving median filters of order 3 and 5.
- Moving average filters using a lag of 3 and 5 samples.

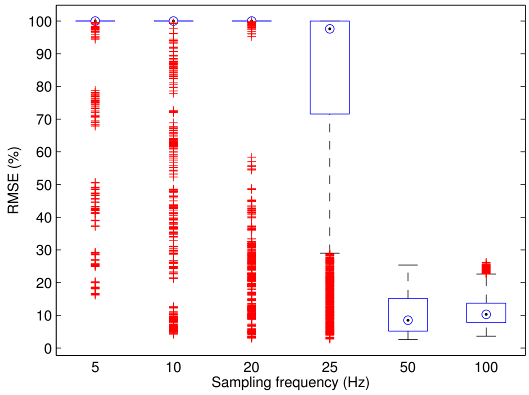

Figure 2: Error distribution for each tested combination, grouped by sampling frequency.

- Low-pass Butterworth filters of 3^{rd}, 5^{th}, 7^{th} and 9^{th} order and cutoff frequencies between 5.5 Hz and 7 Hz.

3.4 Step detection performance

In order to study the variation of the step detection algorithm's accuracy, the complete set of datasets was processed by each different possible combination of the previously defined values of sampling frequency, signal filtering types and values of the algorithm'S parameters.

The normalized root-mean-square error (RMSE) was used as an error metric to compare the performance achieved by each combination, being the error defined as the difference between the estimated and the actual step count.

4 RESULTS AND DISCUSSION

In order to represent the aggregated data from the test run, box-and-whisker diagrams are used. In this kind of diagrams, the bottom and top of the boxes are the first and third quartiles, the circles with a dot inside the box represent the medians, and the "whiskers" are the minimum and maximum of all data, considering as outliers (drawn as crosses) the points that are larger than $Q3 + 1.5 * (Q3 - Q1)$ or smaller than $Q1 - 1.5 * (Q3 - Q1)$, where Q1 and Q3 are the first and third quartiles, respectively.

4.1 Effects of the sampling frequency

The distributions of the errors obtained for each tested combination, grouped by sampling frequency, are represented in Figure 2.

For the 5 Hz sampling frequency, the minimum RMSE obtained (16.20 %) is much larger than for the rest of sampling rates (lower than 4.23 %). Since the normal pedestrian step frequency is around 2 Hz, the 5 Hz sampling rate is close to the Nyquist frequency and problems of signal aliasing are likely to arise.

For the rest of sampling frequencies, although their minimum RMSE's are similar, taking a look at how the errors are distributed it can be seen that, on one hand, lower sampling frequencies are more dependent on the selection of the values of the algorithm's parameters. In fact, the 75% of the tested combinations for 10 Hz and 20 Hz sampling frequencies and the 50% for 25 Hz are completely useless (i.e., 100% RMSE). On the other hand, 50 Hz and 100 Hz sampling rates offer almost equivalent performances.

Therefore, a good algorithm's parameters tuning allows a reduction of the sensors sampling frequency, what leads to a power saving. However, if a very low sampling frequency is selected, a little drift from the optimal tuning will produce big errors.

4.2 Effects of the filtering

Figure 3 shows the distribution of the errors obtained for each type of filter, grouped by three different sampling frequencies.

As it can be seen, the application of a filter to the sensors data improves the performance achieved by the step detection algorithm in all the cases. The best results are obtained applying a 9th order low-pass Butterworth filter, with a cutoff frequency of 6Hz, but its usage is very dependent on the sampling frequency: for the lowest frequency, 25 Hz, the performance is much worse.

Therefore, the appliance of a smoothing filter, as a moving median or moving average, is always recommended. However, for high sampling rates, a frequency domain filter, as a low-pass Butterworth filter, can get better results.

5 CONCLUSIONS

Literature about PDR-based systems usually focuses on describing the detection and estimation algorithms, providing few details about how the configuration of the sensors affects their performances. This work has studied the effects of sensors's sampling frequency and the filtering of their output signals on the accuracy of the step detection algorithm of a wrist-worn IMU based PDR system.

Results have shown that using sampling frequencies larger than a certain threshold (5 Hz in the

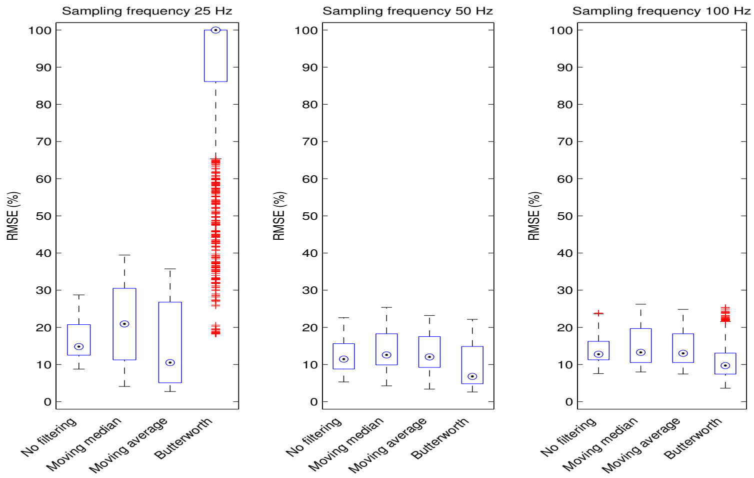

Figure 3: Error distribution for each tested combination, grouped by filtering method.

case studied), similar error rates can be obtained. This is important for implementing PDR systems in battery-supported devices, since reducing the sensors sampling rate implies reducing the power consumption. However, the usage of low sampling frequencies requires a finer tuning of the algorithm's parameters. Otherwise, performance gets dramatically worse.

It has also been seen that the application of filters to the IMU's signals is always recommended because the accuracy is slightly improved. Both smoothing and frequency selective filters can be used, being the latter ones which better accuracy offer for high sampling frequencies.

In the future, this study will be extended to the other two main blocks of a PDR system, the step length and heading estimation, in order to balance the rate accuracy/consumption of the whole positioning system.

Acknowledgments

This work has been supported by the Spanish Ministry of Economy and Competitiveness under the ESPHIA project (TIN2014-56042-JIN).

References

[1] P. A. Zandbergen, "Accuracy of iPhone Locations: A Comparison of Assisted GPS, WiFi and Cellular Positioning," Trans. GIS, vol. 13, pp. 5–25, Jun. 2009.

[2] N. El-Sheimy and X. Niu, "The Promise of MEMS to the Navigation Community," InsideGNSS, p. 11, 2007.

[3] R. Harle, "A Survey of Indoor Inertial Positioning Systems for Pedestrians," IEEE Communications Surveys & Tutorials, vol. 15, no. 3, pp. 1281–1293, Jul. 2013.

[4] D. H. Titterton, J. L. Weston, Institution of Electrical Engineers., and American Institute of Aeronautics and Astronautics., Strapdown inertial navigation technology. Stevenage: Institution of Electrical Engineers, 2004.

[5] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," Comput. Graph. Appl. IEEE, vol. 25, no. 6, pp. 38–46, Nov. 2005.

[6] A. Brajdic and R. Harle, "Walk detection and step counting on unconstrained smartphones," 2013, p. 225.

[7] W.-W. Kao, C.-K. Chen, and J.-S. Lin, "Step-length Estimation Using Wrist-worn Accelerometer and GPS," presented at the International technical Meeting; 24th, Institute of Navigation, 2011.

[8] J. Qian, J. Ma, L. Xu, R. Ying, W. Yu, and P. Liu, "Investigating the use of MEMS Based Wrist-worn IMU for Pedestrian Navigation Application," presented at the International Technical Meeting; 26th, Institute of Navigation; ION GNSS 2013, 2013.

[9] A. Bahillo, A. Arambarri, I. Angulo, E. Onieva, P. Elejoste, and A. Perallos, "Implementing a Pedestrian Tracker Using Low-Cost Bluetooth Inertial Sensors," in Ubiquitous Computing and Ambient Intelligence. Personalisation and User Adapted Services, R. Hervás, S. Lee, C. Nugent, and J. Bravo, Eds. Springer International Publishing, 2014, pp. 1–8.