Measurement: Sensors 18 (2021) 100346

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

A low-cost machine learning process for gait measurement using biomechanical sensors

ARTICLE INFO

Keywords
Machine learning
PIR
Depth camera
Home monitoring
Gait measurement

ABSTRACT

Continuous gait measurement can bring relevant indicators for healthcare professionals. Several techniques were developed for this cause. However, the beneficiaries, especially senior adults, find it hard to accept a monitoring device as it takes away their privacy. In this paper, we present a non-intrusive, low-cost and easy to implement model for gait measurement at home. It consists of implementing 4 passive infrared (*PIR*) sensors facing each other by pair. Our approach is based on a Deep Learning (DL) model that takes as input the signals generated by the *PIR* sensors, as they are representative of the distance and the speed of the moving object. A temporary Depth camera is used for training the model on the gait parameters. To evaluate our approach, we conducted multiple series of experiments on real sensor data. The results are promising and show that our approach is efficient for continuous gait measurement.

1. Introduction

Gait impairment in elderly people is a major issue that widen the gap between overall life expectancy and disability-free life expectancy. Several studies [1–5] have suggested that continuous gait analysis provides a relevant predictor for the quality of life, cognitive disorders, fall risk, among other "good health" indicators.

For such individuals, gait assessment is usually performed in clinical settings characterized by intermittent observations, with the assistance of a healthcare professional and under specific task-oriented conditions [6]. This might introduce a bias because the observations are completely uncorrelated with the familiar environment or because the subject is often stressed out by the test or uses compensation strategies.

Thus, in-home measurement can provide meaningful information for the practitioner to analyze the patient's condition. But also, to be alerted of a favorable evolution in order to evaluate the relevance of the treatment (e.g., balance workshops), or unfavorable (e.g., the need of additional treatments). Current gold-standards systems for motion capture, using cameras and infrared markers placed on bony landmarks [7] (e.g., Vicon, CODA motion) are often expensive, labor intensive and time-consuming to setup. Besides, obstruction of the field of views or lighting confounds issues are limiting factors that make such solutions impracticable for clinical use. Markerless gait measurement [8,9] can be done with RGB cameras and Depth sensors. Yet, these solutions are found to be intrusive by the beneficiaries. Body-worn devices [10] (e.g., Inertial Measurement Units (IMU) based systems within smartwatches) are often perceived as stigmatizing by the senior users or have low acceptability ratings. There are also solutions implemented on or under the floor [11]. But these, although promising and accurate, require the renovation of the home and are quite expensive.

Within the context of aging at home, the setup must be 1) simple, not requiring the intervention of a skilled person, 2) low-cost for a wide deployment, 3) accurate enough so that the interpretation of the measurements is possible and sufficiently relevant, 4) non-intrusive and non-stigmatizing. Points 2 and 3 are often in conflict. However, it can be assumed that for an analyst, greater imprecision can be largely compensated by continuous home measurement.

In view of the constraints listed above, we sought for a non-wearable sensor, off the shelf and inexpensive, which can be placed anywhere in the home. Systems based on passive infrared sensors (*PIR*) attracted much attention due to their advantages of low power consumption, low cost and privacy protection. Our approach aims to use such sensors to evaluate the gait in an indoor environment. It is based on the signals generated by these sensors since they provide significant information on the detected object. Being passive, they do not interfere with each other, which facilitates their implementation.

PIR sensors, whose sensing principle is based on the direct thermoelectric effect, are commonly used to detect movement in a room. Although the output is often binary, common devices incorporate differential detection analog signals (e.g., detection of changes or differences in an ambient reading), which can be retrieved. In the home monitoring context, some approaches were based on this type of sensors to detect falls [12,13]. Others exploit life habits and more precisely changes in habits [14], to alert in case of an unusual absence of movement. To the best of our knowledge, the existing solutions, although interesting, do not measure the biomechanical aspects.

The remainder of this paper is organized as follows: Section 2 presents the desired parameters to be measured by our system. Section 3 presents the output signals of the PIR sensors. Section 4 describes the process of the gait parameters measurement from the output signals, using a deep learning model. Section 5 presents the experimental results and discusses the latter with respect to the uncertainty of the measurements. Finally, section 6 concludes the paper and presents our perspectives.

https://doi.org/10.1016/j.measen.2021.100346

Available online 24 September 2021

2. Measured gait parameters

In this study, we used a RealSense L515 depth camera in order to ensure a correct tracking of the skeleton model. The captured depth images were processed at an approximate rate of 30 frames per second. Gait speed S_{gait} is the variable of interest. It is calculated using the basic formula:

$$S_{gait} = \frac{\Delta P_{cg}}{\Delta t} \tag{1}$$

where P_{cg} represents the center of gravity's position of the human body, calculated by:

$$P_{cg} = Avg\left(p_{shoulders}, p_{hip}\right) \tag{2}$$

where $p_{shoulders}$ and p_{hip} represent the center of gravity of shoulders and hips, respectively.

However, others parameters also seem to be interesting to assess such as the step length, stride length, and stride width. A step is defined by three phases. First, both legs are stable, with a null speed. Then, one of them starts moving with a speed S_{step} and finally they both go back to stable. We consider that the walking speed is steady, so S_{gait} is equivalent to S_{step}. From the Depth camera, a step is identified when S_{gait} is greater than 0.01 m/s. Step length is calculated using the formula:

$$L_{step} = \frac{\Delta P_{cg}}{N_{steps}}; \; S_{gait} > 0.01 \text{ m} \Big/ \text{s} \tag{3}$$

A stride is defined by the distance between two successive contacts on the floor with the same foot. Thus, stride length is the sum of two successive steps length. Lastly, stride width is defined by the projection of foot *b* onto a line defined by the foot's stride *a*. This distance is calculated in (4):

$$W_{stride,a} = \left\| p_{cg,b} - p_{cg,bproj} \right\| \tag{4}$$

The idea behind our work is to measure these gait parameters using a non-intrusive, inexpensive and easily implemented device. In the following sections, we will demonstrate the possibility to achieve a satisfactory accuracy using a *PIR* sensor as biomechanical sensor.

3. PIR-based system output signals

The chosen *PIR* sensor is a Panasonic EKMC2605112, chosen for its ability to give an analog signal and its fair cost. Being used for accurate human body detection, it has a high sensitivity with the disadvantages of a low signal-to-noise ratio (SNR <25), a signal saturation in standard operating conditions and a rare occurrence of a sudden outbreak output. Nevertheless, the signals generated by such sensor can be representative of underlying parameters.

When a human is walking near a *PIR* sensor, as shown in Fig. 1, the produced signal is in a form of a wave packet (see Fig. 2.) at a given time with a given amplitude, frequency and duration. The usual way to assess the gait speed is to measure the time difference between the wave packets acquired by 2 sensors (e.g., *PIR0* and *PIR2*). But, at a given distance from the sensor, the wave packet frequency depends on the speed and can be used as an additional source. As the wave packet frequency also depends on the distance from the sensor, 2 more *PIR* sensors are added close to the first pair. The positioning is shown in Fig. 1.

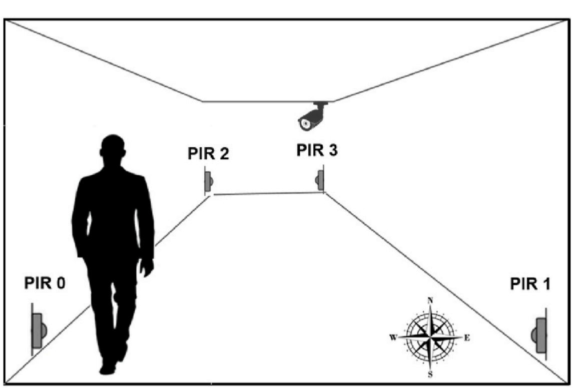

Fig. 1. PIR sensors and Depth camera implementation.

For a better understanding of the produced signals, a wavelet transform had been performed. The scalograms shown in Figs. 3 and 4 represent the wavelet power levels for different scenarios: walking on east, center or west side, with a slow, normal or fast speed. We can clearly see the decrease in frequency due to distance, and somehow the one due to speed. As the gait parameters cannot be directly retrieved from the *PIR*s, a DL model is implemented for this aim.

4. Proposed approach

In this work, we propose a model for continuous gait measurement, based on two pairs of *PIR* sensors and a Depth camera (Fig. 1.). Our approach consists of implementing a DL regression model. It takes as input the signal from the two pairs of *PIR* sensors and computes the gait parameters. These latter are calculated by the Depth camera using formulas (1) - (4) and are fed to the DL model. In addition, the accurate gait parameters are obtained by using the camera as the ground truth of the experiment. It is also a temporary device used for the training phase only, thus the beneficiary's privacy is preserved. Research work presented in Refs. [15,16] motivated us for this approach.

In a nutshell, the proposed model works as follows: The Depth camera will calculate the gait parameters as a person walks by. Simultaneously, the output signals of *PIR* sensors are processed and three parameters are extracted from each. Then, a DL model takes the values of *PIR* sensors as input to predict the ones given by the camera.

4.1. Experimental setup

200 experiments on real sensor data were conducted for a duration of one and a half hour. The experiments were carried out in a corridor of dimensions 1.77 m × 5 m. We placed two pairs of *PIR* sensors facing each other, separated by a distance of 2 m and placed at the ankle height (Fig. 1.). The camera was positioned at the origin of the path to capture the whole body skeleton. The two types of sensors were synchronized with a start signal. For a heterogeneous dataset, the participants were asked to walk with a slow, normal and fast gait speed. In addition, three

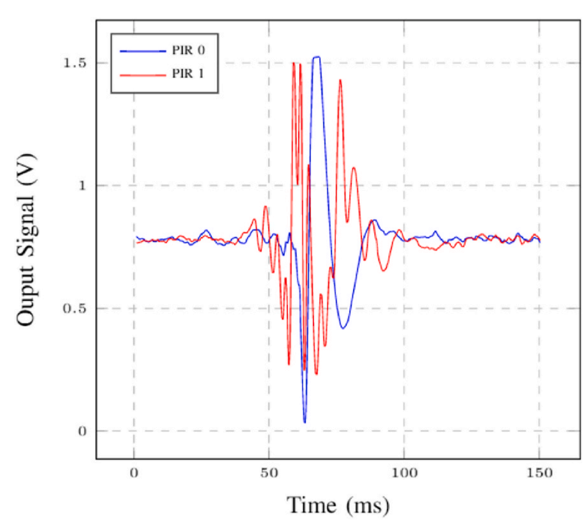

Fig. 2. Example of the output signals from a pair of *PIR* sensors.

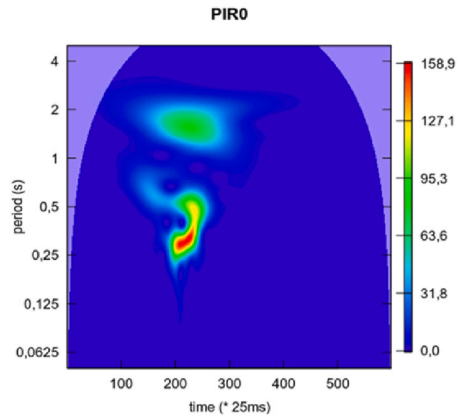

Fig. 3. Wavelet power levels from different distances (west and east, respectively).

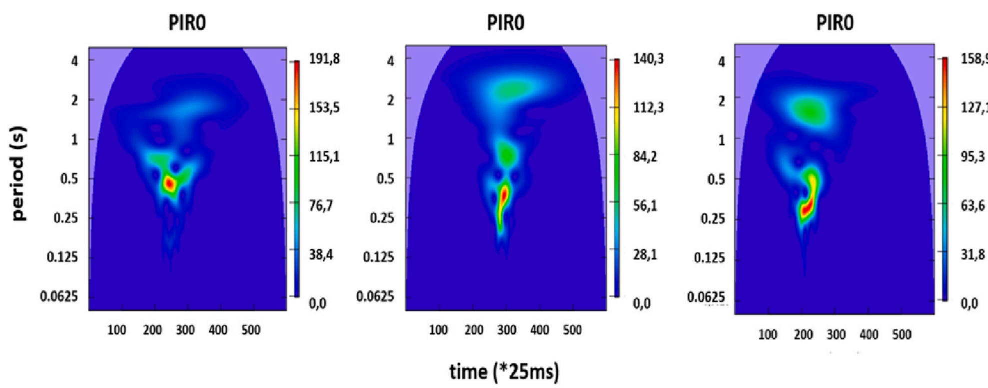

Fig. 4. Wavelet power levels for different speeds.

different walking paths were adopted: east, center and west. The measurements were carried out on different days in order to counteract light bias and the clothing worn.

4.2. Deep learning model

The purpose of our approach is to create an autonomous gait measurement model for home monitoring. The idea is to measure gait parameters based on the output signals of 4 *PIR* sensors. For this aim, we used a Multi-Layer Perceptron (MLP) regressor as a benchmark model. It takes as input a dataset of the different signal characteristics and as output the parameters calculated by the camera. The parameters used for our model are listed in Table 1. We would like to emphasize that before running our prediction model, we calculated the coefficient R^2 as well as the p-value to ensure that our independent and dependent variables do not suffer from multicollinearity.

5. Results and discussion

We considered the gait speed P_{cg}, the step length L_{step} and the stride width W_{stride}, calculated using the RealSense L515, as ground truth values. In order to identify how close the measured results are from the real ones, the Average bias and the Root Mean Square Error (RMSE) are computed in Table 2 using formulas (5) and (6), respectively.

$$Average\ bias = \frac{1}{n}\sum_{i=1}^{n}(x[i] - y[i]) \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x[i] - y[i])^2} \tag{6}$$

Table 1
MLP parameters.

Model parameters	Values
Hidden layers	3
Neurons per layer	200
Max_iter	5000
Random_state	50
Solver	'adam'
Activation function	'relu'
Initial learning rate	0.0005

Table 2
MLP model evaluation.

Gait parameters	Average bias	Range	RMSE
Speed (m/s)	−0.002	[0.367; 1.994]	0.171
Step length (m)	−0.024	[0.036; 0.848]	0.116
Stride width (m)	−0.009	[0.025; 0.389]	0.075

where n is the number of samples; x and y are two vectors representing the set of indication values given by the *PIR* sensors and the depth camera, respectively.

The measured gait parameters are shown in Fig. 5. We notice that the values of gait speed and step length are accurately measured with a standard uncertainty relevant with a day-to-day monitoring of these indicators. Thus, the prediction model fits well these parameters. Nevertheless, it was less able to measure the stride width.

With a series of continuous measurements, our system can easily adjust to fall within the bounds of measurement error [17]. The uncertainty can be explained by the presence of noise and spikes in the *PIR*

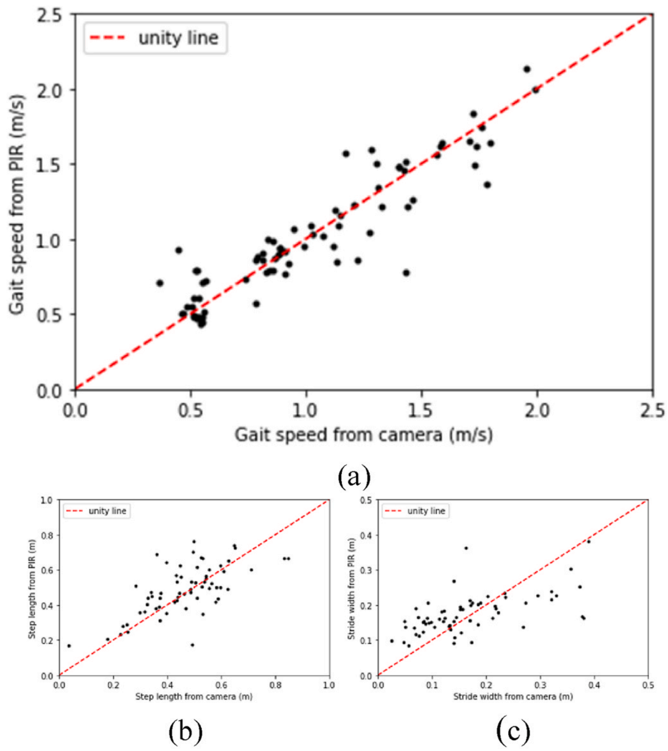

Fig. 5. Results: a) gait speed b) stride length and c) stride width compared to the depth camera measurements.

signals. As discussed in Section 3, *PIR* sensors are extremely sensitive with a SNR less than 25. In such case, the model will assume that the erroneous signal corresponds to the speed given by the camera. Moreover, we must underline the fact that the *PIR* sensors are trained by the Depth camera, which itself is a sensor that may be affected by environmental factors (e.g., light). In addition, the camera presents a depth accuracy between 5 mm and 14 mm through 9 m as specified by its manufacturer.[1] Thus, the proposed experiment, despite its uncertainty, is deemed to be effective for gait speed and step length measurements.

6. Conclusion and perspectives

In this work, a simple yet effective gait measurement approach has been proposed. It is based on two pairs of *PIR* sensors along with a temporary Depth camera. Although *PIR* sensors are usually used for human presence detection, we demonstrated that they can be a used for gait measurement. They can also be a potent solution for both the acceptability issue of continuous monitoring devices, as well as their high costs. Once the sensor network detects a moving object, each *PIR* generates a signal of different amplitude, frequency and duration. These signal variations are fed to a MLP deep learning algorithm. The Depth camera extracts the corresponding gait speed, step length and stride width from each depth image and the prediction model is trained accordingly. Once the training phase is over, the Depth camera is removed and the measurement system will easily be forgotten by the concerned person.

Future work consists of finding the optimal sensors height from the ground and disposition, for better precisions related to stride width. Also, we aim to implement an additional feature for identity recognition, in order to use such system in a multi-residential home.

Acknowledgments

This work was supported by Savoie Mont Blanc Council.

References

[1] K. Saho, K. Uemura, M. Matsumoto, Screening of mild cognitive impairment in elderly via Doppler radar gait measurement, IEICE Commun. Exp. 9 (1) (2020) 19–24.
[2] A. Mihailovic, R.M. De Luna, S.K. West, D.S. Friedman, L.N. Gitlin, P.Y. Ramulu, Gait and balance as predictors and/or mediators of falls in glaucoma, Invest. Ophthalmol. Vis. Sci. 61 (3) (2020), 30–30.
[3] K. Saho, K. Shioiri, M. Fujimoto, Y. Kobayashi, Micro-Doppler radar gait measurement to detect age-and fall risk-related differences in gait: a simulation study on comparison of deep learning and gait parameter-based approaches, IEEE Acc. 9 (2021) 18518–18526, https://doi.org/10.1109/ACCESS.2021.3053298.
[4] F. de Oliveira Silva, J.V. Ferreira, J. Plácido, D. Chagas, J. Praxedes, C. Guimarães, L.A. Batista, J. Laks, C. Deslandes, Gait analysis with videogrammetry can differentiate healthy elderly, mild cognitive impairment, and Alzheimer's disease: a cross-sectional study, Exp. Gerontol. 131 (2020), 110816, https://doi.org/10.1016/j.exger.2019.110816.
[5] B. Noh, C. Youm, M. Lee, H. Park, Age-specific differences in gait domains and global cognitive functioning older women: gait characteristics based on gait speed modification, PeerJ 8 (2020), e8820.
[6] A.K. Stuck, M. Bachmann, P. Füllemann, K.R. Joseph-son, A.E. Stuck, Effect of testing procedures on gait speed measurement: a systematic review, PloS One 15 (6) (2020), e0234200.
[7] P. Merriaux, Y. Dupuis, R. Boutteau, P. Vasseur, X. Sa-vatier, A study of vicon system positioning performance, Sensors 17 (7) (2017) 1591.
[8] K. Chapron, K. Bouchard, S. Gaboury, Real-time gait speed evaluation at home in a multi residents' context, Multimed. Tool. Appl. (2020) 1–19.
[9] Q. Guan, C. Li, X. Guo, B. Shen, Infrared signal based elderly fall detection for in-home monitoring, in: in2017 9th International Conference on Intelligent Human-Machine Systems and Cybernetics, vol. 1, IEEE, 2017, pp. 373–376.
[10] R.S. McGinnis, N. Mahadevan, Y. Moon, K. Seagers, N. Sheth, J.A. Wright Jr., S. Di Cristofaro, I. Silva, E. Jort-berg, M. Ceruolo, et al., A machine learning approach for gait speed estimation using skin-mounted wearable sensors: from healthy controls to individuals with multiples clerosis, PloS One 12 (6) (2017), e0178366.
[11] R. Hoffmann, H. Brodowski, A. Steinhage, M. Grze-gorzek, Detecting walking challenges in gait patterns using a capacitive sensor floor and recurrent neural networks, Sensors 21 (4) (2021) 1086.
[12] Z. Liu, M. Yang, Y. Yuan, K.Y. Chan, Fall detection and personnel tracking system using infrared array sensors, IEEE Sensor. J. 20 (16) (2020) 9558–9566.
[13] M.M. Rahman, M.M. Islam, S. Ahmmed, S.A. Khan, Obstacle and fall detection to guide the visually impaired people with real time monitoring, SN Comput. Sci. 1 (2020) 1–10.
[14] Antoine Piau, Benoit Lepage, Carole Bernon, et al., Real-time detection of behavioral anomalies of older people using artificial intelligence (The 3-PEGASE Study): protocol for a real-life prospective trial, JMIR Res. Protocols 8 (11) (2019), e14245.
[15] M. Zhao, Y. Tian, H. Zhao, M.A. Alsheikh, T. Li, R. Hris-tov, Z. Kabelac, D. Katabi, A. Torralba, Rf-based 3d skeletons, in: Proceedings of the 2018 Conference of the ACM Special Interest Group on Data Communication, 2018, pp. 267–281.
[16] S. Aziz Shah, J. Ahmad, A. Tahir, F. Ahmed, G. Russel, S.Y. Shah, W. Buchanan, Q. H. Abbasi, Privacy-preserving non-wearable occupancy monitoring system exploiting wifi imaging for next-generation body centric communication, Micromachines 11 (4) (2020) 379.
[17] Goldberg, S. Schepens, Measurement error and minimum detectable change in 4-meter gait speed in older adults, Aging Clin. Exp. Res. 23 (5) (2011) 406–412.

Farah Abdel Khalek
Univ Savoie Mont Blanc, LISTIC, Annecy, France
Univ Savoie Mont Blanc, SYMME, Annecy, France

Marc Hartley, Eric Benoit*, Stephane Perrin
Univ Savoie Mont Blanc, LISTIC, Annecy, France

Luc Marechal, Christine Barthod
Univ Savoie Mont Blanc, SYMME, Annecy, France

* Corresponding author.
E-mail address: eric.benoit@univ-smb.fr (E. Benoit).

[1] https://www.intelrealsense.com/lidar-camera-l515.