An IoT-Based Method for Collecting Reference Walked Distance for the 6-Minute Walk Test

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Abstract. This paper addresses the need for accurate and continuous measurement of walked distance in applications such as indoor localisation, gait analysis or the 6-minute walk test (6MWT). We propose a method to continuously collect ground truth data of walked distance using an IoT-based trundle wheel. The wheel is connected via Bluetooth Low Energy to a smartphone application which allows the collection of inertial sensor data and GPS location information in addition to the reference distance. We prove the usefulness of this data collection approach in a use case where we derive walked distance from inertial data. We train a 1-dimensional CNN on inertial data collected by one researcher in 15 walking sessions of 1 km length at varying speeds. The training is facilitated by the continuous nature of the reference data. The accuracy of the algorithm is then tested on holdout data of a 6-min duration for which the error of the inferred distance is within clinically significant limits. The proposed approach is useful for the efficient collection of input and reference data for the development of algorithms used to estimate walked distance, such as for the 6MWT.

Keywords: 6MWT · odometer · walk distance · IoT · inertial sensors

1 Introduction

Measuring walked distance is of relevance to several applications, including indoor localisation [1], pedestrian dead reckoning (PDR) [2], gait analysis [3], fitness tracking and medicine [4] and, more broadly, where the main interest is to measure the distance between two points or of a path. In PDR applications, for example, step length is an important parameter used to obtain the subject's location, and a common way to estimate the step length is to divide the walked distance by the number of detected steps [5–7].

Among clinical applications, the walked distance is particularly relevant in the 6-Minute Walk Test (6MWT), a sub-maximal physical capacity exercise that patients, mostly with pulmonary and cardiac diseases, perform to monitor

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the progress or deterioration of their condition [8]. The test is usually run in a clinic and is performed by measuring the distance walked in six minutes, i.e. the 6-Minute Walked Distance (6MWD). The current gold-standard 6MWD is measured either using a trundle wheel or by counting how many laps a patient walks on a 30-m long track, such as a hospital hallway. Technology advances allow the remote execution of this test, thus easing the burden and reducing costs for both clinicians and patients. Additionally, performing the test in patients' natural environments promotes more frequent monitoring [9,10]. Typically Inertial Measurements Units (IMUs) such as accelerometers and gyroscopes are used to measure the 6MWD [11] or, in outdoor environments, the Global Positioning System (GPS) is also often used [12]. However, weather conditions and privacy issues can make this type of environment inconvenient for patients.

To develop and test algorithms for the estimation of walked distance, be it for step length estimation or the 6MWT, a fundamental requirement is the collection of data from human subjects. To allow data collection in natural conditions, for example in indoor environments where positioning is not available or when the walk does not happen on a straight line [6], a simple-to-use, reliable, (semi)automatic approach is needed. Standardised methodologies and datasets do not exist yet for this type of problem [13], therefore the challenge of capturing human mobility information using sensors with unconstrained placement remains open [6].

With this paper, we propose a method to continuously collect IMU and distance data at every meter based on an Internet of Things (IoT)-based trundle wheel which is connected to a mobile phone. The work has four main contributions:

1. An IoT-based trundle wheel which measures the distance in a continuous fashion and sends the measurements over Bluetooth Low Energy (BLE).
2. A smartphone app to collect data from the BLE connected trundle wheel and the sensors embedded in the phone - including IMU (acceleration, rotation rate, orientation) and positioning (such as GPS).
3. A dataset of walking activity, including continuous reference distances, collected by one researcher at different speeds.
4. An example of a Convolutional Neural Network (CNN) model that accurately (compared with reference distance) computes the walked distance using only the inertial sensors data from the smartphone.

This paper is structured as follows: Sect. 2 introduces related work, Sect. 3 describes the methods we employed, Sect. 4 shows the results we have obtained and Sect. 5 discusses and reflects on them. Finally, Sect. 6 summarises our main conclusions based on this research and proposes future directions.

2 Related Work

In the domain of supervised algorithms for estimating walked distance, a multitude of data sources and sensor configurations have been explored, each with its unique considerations. This section explores sensor choices, methods to collect reference distance measurements and distance estimation approaches.

IMUs sensors found in smartphones and wearable devices are common for tracking human activity. Sensor's location on the body affects data patterns [10,14]. In outdoor environments, satellite positioning signals such as the GPS are usually considered [12,15,16], while in indoor environments BLE or WiFi are used to compute walked distances, e.g., in PDR applications [7]. While satellite positioning is considered accurate, smartphone users may find outdoor environments problematic, especially when physical conditions or weather do not allow outdoor activities. This paper focuses on computing the walked distance through smartphone IMU sensors, as this could be used both indoors and outdoors.

To ensure accurate walking distance estimates and compare approaches, it's crucial to consider standardised methods for reference measurements. In the 6MWT, clinical personnel typically count laps walked and measure the remaining distance of the final lap at the end of 6 min [17]. In research settings, a simple but reliable approach involves using a trundle wheel to measure walked distance [12,15]. More complex approaches have been used in other studies, such as video recording or sensorised carpets [18–20]. Providing public datasets including both sensor data and a reference walked distance is thus valuable for developing algorithms that extract the walked distance from the input sensor data. For example, Yan et al. published a dataset comprising 150 min of walking data from individuals who carried smartphones in various body locations, with ground truth positioning obtained via a Visual Inertial Odometry system [21]. However, as highlighted in the review by Diez et al. [13], there is an absence of established methodologies and datasets for step length estimation, notwithstanding the potential of inertial sensor-based algorithm to estimate walked distance [17].

Modelling of walked distance using inertial sensors has been approached with rule-based algorithms such as the one proposed by Capela et al. for the 6MWT [19] and the indoor algorithm proposed by Salvi et al. [12,22] or by means of Machine Learning (ML) models [23], where the latter approach is showing promise within gait analysis [24]. Furthermore, Juen et al. [23] proposed support vector machine models for computing walking speed and to compute 6MWD, obtaining an average 3.23% error. A more sophisticated approach is used by Klein et al. [2], who proposed a framework which outputs a regression value of change in distance or in step length. They used data coming from the public dataset RIDI [21] to train algorithms to estimate step length, either directly or through the change in distance or the Weinberg gain. Of these algorithms, the best performing was the change in distance estimator with an average error of 2.1% on six considered trajectories. The architecture considered as input was the smartphone body location and the raw inertial data which were then fed into a neural network based on a modified version of the ResNet-18 [25].

In this paper, we present both an IoT-trundle wheel for the collection of walked distances useful for supervised modelling approaches and an example of a regression model to estimate the distance from inertial sensor data. This example highlights how the trundle wheel allows the collection of distance information with finer granularity compared to current golden-standard approaches.

3 Materials and Methods

3.1 IoT Trundle Wheel

The IoT trundle wheel was developed at Malmö University using off-the-shelf electronic components. It consists of an electronic board based on the ESP32 chip, a reed switch and a magnet. The reed switch serves as a magnetic sensor: when a magnet passes by the sensor, the switch's blades come into contact with each other allowing current to flow. By attaching the magnet to one spoke of the wheel it becomes possible to detect each revolution of the wheel. The reed switch is connected between the reference voltage (3.3.V) and a GPIO port of the ESP32. The ESP32 and the reed switch are soldered onto a protoboard, which is then attached to the wheel handle using velcro in order to be easily attached and detached as needed. The firmware, running on the ESP32 and developed using the Arduino libraries, counts the number of revolutions of the wheel and transmits the measured distance, one per revolution, to the smartphone via BLE at each wheel revolution. If no wheel revolution is detected for 5 s, the overall walked distance until that time is sent. Figure 1.a provides a visual representation of the trundle wheel with the incorporated components.

3.2 Smartphone Application

The mobile application, developed using the Apache Cordova framework, enables the collection of data from the IoT trundle wheel and the embedded sensors in the phone simultaneously. The collected information is stored in a text file, including data on distance travelled, acceleration, rotation rate, orientation, steps taken, and GPS signal. Figure 1.b shows the main screen of the smartphone application. The user starts data collection by pressing the "connect" button. This scans for nearby BLE devices, connects to the ESP32 board if found, and displays the connection state on the main screen of the app. After connecting, the user can press "Start" which initiates a timer, resets the distance to zero and activates wheel rotation detection on the ESP32. Concurrently, the application writes the sensor data as well as the time at which the data is captured. When completing the walk, the user presses "End" to stop writing to the file and stops reading the IMU and GPS data. The BLE connection remains active until the smartphone Bluetooth is turned off.

3.3 Data Collection

Data used in this research paper correspond to inertial measurements of accelerometer and gyroscope sensors embedded in the smartphone from fifteen recordings made by a single researcher walking outdoors. Each recording corresponds to a walked distance of approximately one kilometre performed while

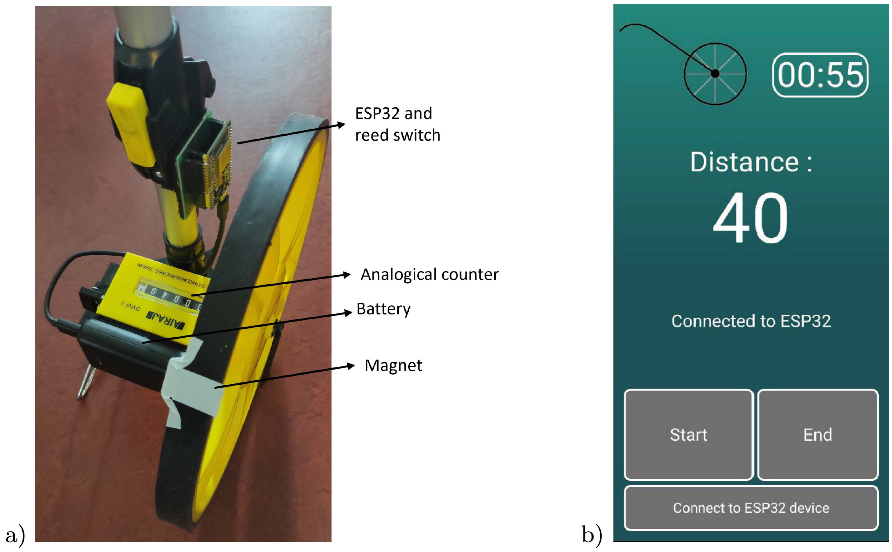

Fig. 1. a) IoT-based trundle wheel and its components, b) Screenshot of the smartphone application to retrieve data.

keeping the smartphone in one hand, and the IoT trundle-wheel in the other hand. The data was recorded with different speeds and waking styles, according to the following protocol: 3 walks at normal speed, 3 walks at fast speed, 3 walks at slow speed, 3 walks at varying speed (from standing still to walking fast), and 3 walks at mixed speed. The dataset, the Arduino code, the smartphone application and the CNN model code are published with an open-source license at https://github.com/Jeremy618/TrundleWheel. An example of recorded acceleration and rotation rate in a 5-second chunk is shown in Fig. 2.

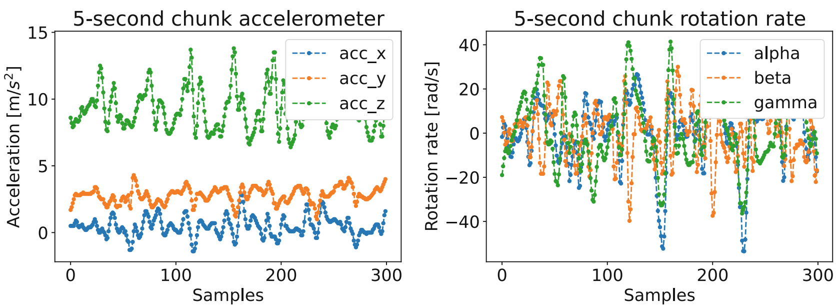

Fig. 2. Acceleration and rotation rate example in a 5-second chunk

3.4 Distance Estimation Algorithm

As an example of how this dataset can be used, we propose a CNN-based model for estimating the walked distance. This example illustrates the potential of having a high-fidelity reference dataset for walked distance estimations. The architecture of the algorithm is represented in Fig. 3 where we considered time windows of 5 s, which would allow us to capture the movement produced by at least 2 or 3 steps. The model input is a $[300 \times 6]$ matrix where the first dimension corresponds to 5 s of recording using a sampling frequency of 60 Hz and the second dimension corresponds to the six input signals of the IMU: three-axial acceleration and three-axial rotation rate. The corresponding output for each input is the distance walked within that segment, which was interpolated from the reference data collected from the IoT trundle wheel.

The model architecture develops through three 1-D convolutional layers to extract relevant features from the provided inputs [26]. These layers are interspersed with batch normalisation, max pooling and dropout layers. The convolutional layers employ a Rectifier Linear Unit (ReLU) activation function, have kernel sizes of 32, 16, and 3, and a number of filters of 64, 32, and 8 respectively. The max pooling layer uses a pooling size of three. The network ends with a flattening layer and a dense layer with a single unit which provides the desired output of dimension 1 (one distance per input). To develop the model architecture, we considered examples of CNNs fed with inertial sensors from previous work that studied activity recognition using inertial sensors [27,28]. However, since these tasks were different, we empirically selected the model's hyper-parameters as the number of filters and kernel size, epochs, batch size, and the number of considered convolutional layers.

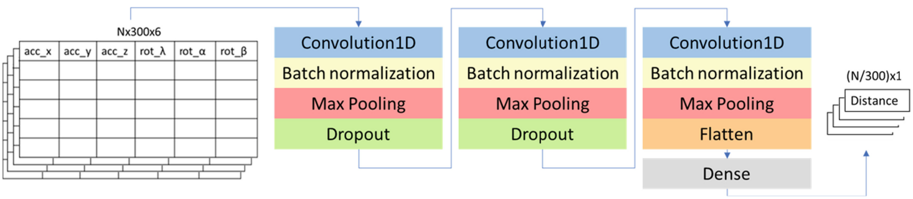

Fig. 3. CNN model architecture. Input data corresponds to three-axial accelerometer and gyroscope, while the output is the walked distance every 5 s.

To evaluate model performances throughout the training process, the Mean Square Error (MSE), the loss function and the Mean Absolute Error (MAE) are monitored. The model is trained over 150 epochs with a batch size of 32. Data were initially divided into two primary sets: one for cross-validation (54.83%) and the other for holdout testing (45.17%). The holdout test data covers the first six minutes of each recording. Nevertheless, the model is suitable to estimate distance in any time window, and can therefore be applied to other purposes (e.g., a 2-minute walk test, which is sometimes used in clinical practice). The model is trained using a 5-fold cross-validation, which, at each iteration, separates the data into training set (53.5%), validation set (13.2%), and test set (33.3%). Early stopping is used to mitigate overfitting while training. Of the five obtained models, the one which performs the best on the test data of the respective fold is selected and is used to predict the outcomes from holdout test data and related statistics. Holdout estimation results are finally evaluated by examining various error statistics, including the Mean Absolute Percentage Error (MAPE) and the Bland-Altman limits of agreement. This approach allows for a meaningful comparison with results from the existing literature, including applications for the 6MWT.

4 Results

Data includes 15 walks in the city of Malmö (Table 1), gathered by a healthy researcher using a Xiaomi Redmi Note 9 Pro smartphone. Electronic and mechanical measurements matched, verifying reliability. In Fig. 4 we observe that the absolute errors mostly stay below three meters in a 5-s time window, and they remain below 30 m in a 6-min duration, except for one instance reaching 34.53 m. Key evaluation metrics are presented in Table 2. Among other promising statistical results, the correlation between the estimated distance and the ground truth distance is 0.93 for the 5-second chunks and 0.99 for the 6-min duration. Performance variations can be attributed to factors like variations in speed, walking style and the presence of noise and confounders, such as the way the phone was held and how the arms were moving.

Table 1. Statistics on collected data.

	Mean	STD	Max	Min
Recordings distance [m]	1005.39	5.74	1014.98	999.99
Recordings duration [s]	796.79	133.08	1058.14	581.43
Sampling frequency [Hz]	59.92	0.04	59.96	59.83

5 Discussion

This paper proposes a method to collect walked distance reference values by using an IoT trundle wheel and a smartphone app. The IoT-trundle wheel is composed of a conventional trundle wheel with commercially available electronics components mounted to it. It is possible to use the IoT-trundle wheel both indoors and outdoors, as well as for trajectories that are not straight lines since the distance is measured even when a user makes turns. This approach allows users to walk in more natural conditions, with any kind of desired walk pattern

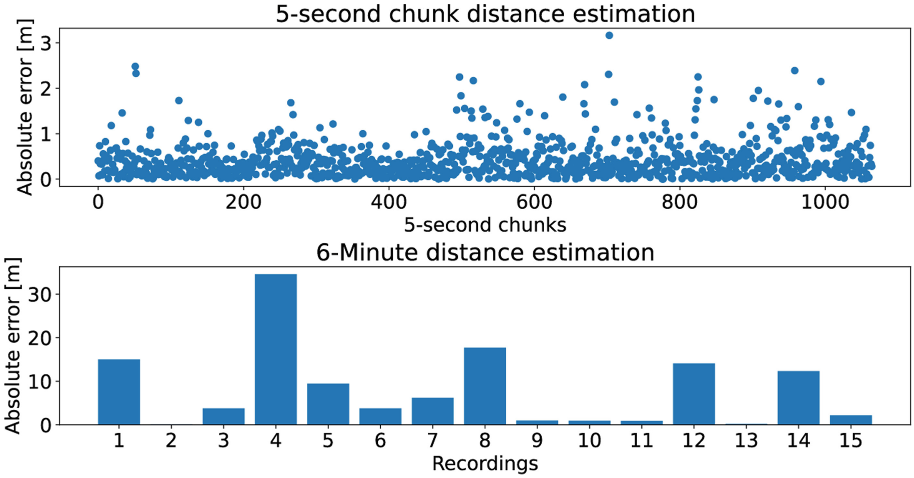

Fig. 4. Absolute error of the estimated distance for the holdout test data (first 6 min of every recording). Results are shown for the 5-second chunks and for the whole 6-minute distance.

Table 2. 5-second chunk and 6-minute statistics of the error computed as the difference between the reference value and the estimated one. All values are in meters. MAPE is not available for 5-second chunks because of the presence of zeros.

	5-second chunk	6-minute cumulative
MSE	0.33	149.73
RMSE	0.57	12.24
ABS median	0.31	3.79
ABS mean	0.41	8.15
ABS SD	0.4	9.12
ABS min	0	0.11
ABS max	3.16	34.53
CORR	0.93	0.99
MAPE	–	1.97
LoA_low	−1.15	−25.80
LoA_high	1.10	21.38

and speed. It, however, requires keeping the trundle wheel in one hand, which makes it not suitable for people who require walking support. The IoT trundle wheel produces distance information at each revolution of the wheel, thus at each meter. Considering that the average walking speed of an healthy adult is 4.5 km/h (1.25 m/s), we can estimate the trundle wheel sampling frequency as 1.25 Hz. Thus, we consider both spatial resolution (1 m) and sampling frequency (1.25 Hz) as acceptable for the purposes of measuring human walking activity.

As a proof of concept, we used collected inertial data from one researcher to understand the usefulness of this approach in the case of smartphone-based walked distance measurement, for example in a 6MWT. Our dataset is provided publicly and includes global positioning and inertial measurements together with reference distance. Similarly, Yan et al. [21] have published a dataset of inertial data and positioning references. To collect their ground truth data, Yan et al. used a setup involving a visual inertial odometry system, requiring the smartphone camera to always have a clear field-of-view, a constraint which is not required in our simpler solution. However, their dataset focuses on positioning, which is richer in information than just the distance.

We use our data to train a CNN-based algorithm for estimating distance in 5-second chunks. Combining these chunks into 6-min duration tracks results in an average absolute error of 8.15 m with limits of agreement of −25.80 and 21.38 m. within the clinically accepted range of 30 to 50 m for various health conditions [29–31], thus validating the potential of the approach and showing the relevance for clinical applications.

Compared to other studies reported in the literature, our algorithm performs similarly or better. For example, a study from Juen et al. [23] proposed a model trained on a walking lap with fixed distance and it estimates walked distance in a 6MWT with a 3.23% error. The percentage error that we obtained not only is smaller (MAPE: 1.97%) but also allows for distance estimation at any path length. Our obtained errors are also smaller than Klein et al. [2] (2.1%) who proposed a regression model predicting change in distance along six different trajectories.

Capela et al. [19] achieved a better result with an average percentage difference of 0.12%. However, they used a smartphone attached to a waist belt, which reduces noise and motion artefacts, whereas we opted for a more user-friendly approach of holding the phone in one hand, better suited for natural environments.

An inertial-based algorithm for 6MWT was proposed in [12,22]. Their indoor approach reached Bland-Altman limits of agreement of −133.35 to 162.55 m, which are significantly higher than ours. Their tests were conducted imitating a classic 6MWT, that is, walking back and forth a walkway, whereas our approach allows a more natural walking activity. It has to be noted, however, that their tests included different users and mobile phones, whereas our example only employed one user and one smartphone. They also developed an algorithm based on GPS data which could inspire future developments, i.e., mixing both positioning and inertial data for higher accuracy.

5.1 Limitations and Future Works

Our data collection method is limited to estimating walked distance, in addition, the data are restricted to one user and smartphone, limiting its generalizability. Despite these limitations, we see our approach as a promising proof of concept that highlights the data's potential applications and the need for further research in this direction.

This work provides a foundation for multiple directions to be developed in the future. For example, given the open challenge of step length estimation, heading towards its estimation is likely to be relevant. A more thorough dataset involving several users, different mobile phones and walking styles would be needed to be able to assess the extent to which supervised algorithms can estimate walked distance on a wide population. The algorithm was developed by only using a CNN architecture to obtain a proof-of-concept model on this type of data. Further exploration is necessary to improve the model by considering hyperparameter tuning and other Deep Learning (DL) approaches such as the use of recurrent layers like in Long Short-Term Memory (LSTM). Some simplifications of the model should also be considered, for example, considering the magnitude of the signals, instead of the three axial components, or using data augmentation techniques [27,32].

6 Conclusions

This article presents a novel approach to continuously measuring walking activity, using IMU sensors and positioning data while providing reference walked distance throughout the whole path. The results show that this approach performs as well or better than existing methods, particularly in the context of the 6MWT. It offers enhanced reliability and information, enabling distance measurements in diverse, natural settings, indoors and outdoors, facilitating continuous and unobtrusive health monitoring.

While this study illustrates the potential of this approach, it suffers from limitations related to a single user and smartphone. The results should be viewed as groundwork for future research in the field.

References

1. Mariakakis, A.T., et al.: SAIL: single access point-based indoor localization. In: Proceedings of the 12th Annual International Conference on Mobile Systems, Applications, and Services, pp. 315–328 (2014)
2. Klein, I., Asraf, O.: StepNet–deep learning approaches for step length estimation. IEEE Access **8**, 85706–85713 (2020)
3. Wang, J.-S., et al.: Walking pattern classification and walking distance estimation algorithms using gait phase information. IEEE Trans. Biomed. Eng. **59**(10), 2884–2892 (2012)
4. Xie, J., et al.: Evaluating the validity of current mainstream wearable devices in fitness tracking under various physical activities: comparative study. JMIR Mhealth Uhealth **6**(4), e9754 (2018)
5. Ho, N.-H., Truong, P.H., Jeong, G.-M.: Step-detection and adaptive step-length estimation for pedestrian dead-reckoning at various walking speeds using a smartphone. Sensors **16**(9), 1423 (2016)
6. Yang, Z., et al.: Mobility increases localizability: a survey on wireless indoor localization using inertial sensors. ACM Comput. Surv. **47**(3), 1–34 (2015). https://doi.org/10.1145/2676430. ISSN 0360-0300, 1557-7341

7. Kunhoth, J., et al.: Indoor positioning and wayfinding systems: a survey. Hum.-centric Comput. Inf. Sci **10**(1), 1–41 (2020)
8. Enright, P.L.: The six-minute walk test. Respir. Care **48**(8), 783–785 (2003)
9. Mak, J., et al.: Reliability and repeatability of a smartphone-based 6-min walk test as a patient-centred outcome measure **2**, 77–87 (2021). https://doi.org/10.1093/ehjdh/ztab018. ISSN 2634–3916
10. Pires, I.M., et al.: Development technologies for the monitoring of six-minute walk test: a systematic review. Sensors **22**(22), 581 (2022). https://doi.org/10.3390/s22020581. ISSN 1424-8220
11. Storm, F.A., et al.: Wearable inertial sensors to assess gait during the 6-minute walk test: a systematic review. Sensors **20**(9), 2660 (2020)
12. Salvi, D., et al.: The mobile-based 6-minute walk test: usability study and algorithm development and validation. JMIR mHealth uHealth **8**(1), e13756 (2020). https://doi.org/10.2196/13756. Company: JMIR mHealth and uHealth Distributor: JMIR mHealth and uHealth Institution: JMIR mHealth and uHealth Label: JMIR mHealth and uHealth publisher: JMIR Publications Inc., Toronto, Canada
13. Díez, L.E., et al.: Step length estimation methods based on inertial sensors: a review. IEEE Sens. J. **18**(17), 6908–6926 (2018)
14. Kunze, K., Lukowicz, P.: Sensor placement variations in wearable activity recognition. IEEE Pervasive Comput. **13**(4), 32–41 (2014). https://doi.org/10.1109/MPRV.2014.73
15. Ziegl, A., et al.: mHealth 6-minute walk test – accuracy for detecting clinically relevant differences in heart failure patients. In: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pp. 7095–7098, November 2021. https://doi.org/10.1109/EMBC46164.2021.9630118
16. Gray, A.J., et al.: Validity and reliability of GPS for measuring distance travelled in field-based team sports. J. Sports Sci. **28**(12), 1319–1325 (2010)
17. Shah, V.V., et al.: Inertial sensor algorithm to estimate walk distance. Sensors **22**(33), 1077 (2022). ISSN 1424–8220. https://doi.org/10.3390/s22031077
18. Li, S.-H., et al.: Design of wearable and wireless multi-parameter monitoring system for evaluating cardiopulmonary function. Med. Eng. Phys. **47**, 144–150 (2017)
19. Capela, N.A., Lemaire, E.D., Baddour, N.: Novel algorithm for a smartphone-based 6-minute walk test application: algorithm, application development, and evaluation. J. NeuroEng. Rehabil. **12**(1), 19 (2015). https://doi.org/10.1186/s12984-015-0013-9. ISSN 1743–0003
20. A smartphone approach for the 2 and 6-minute walk test. In: Chicago, IL, August 2014, pp. 958–961 (2014). https://doi.org/10.1109/EMBC.2014.6943751. http://ieeexplore.ieee.org/document/6943751/. ISBN 978-1-4244-7929-0
21. Yan, H., Shan, Q., Furukawa, Y.: RIDI: robust IMU double integration. In: Ferrari, V., Hebert, M., Sminchisescu, C., Weiss, Y. (eds.) ECCV 2018. LNCS, vol. 11217, pp. 641–656. Springer, Cham (2018). https://doi.org/10.1007/978-3-030-01261-8_38
22. Salvi, D., et al.: App-based versus standard six-minute walk test in pulmonary hypertension: mixed methods study. JMIR Mhealth Uhealth **9**(6), e22748 (2021)
23. Juen, J., Cheng, Q., Schatz, B.: A natural walking monitor for pulmonary patients using mobile phones. IEEE J. Biomed. Health Inform. **19**(4), 1399–1405 (2015)
24. Caldas, R., et al.: A systematic review of gait analysis methods based on inertial sensors and adaptive algorithms. Gait Posture **57**, 204–210 (2017)
25. He, K., et al.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778 (2016)

26. Zhao, B., et al.: Convolutional neural networks for time series classification. J. Syst. Eng. Electron. **28**(1), 162–169 (2017)
27. Caramaschi, S., Papini, G.B., Caiani, E.G.: Device orientation independent human activity recognition model for patient monitoring based on triaxial acceleration. Appl. Sci. **13**(7), 4175 (2023)
28. Fridriksdottir, E., Bonomi, A.G.: Accelerometer-based human activity recognition for patient monitoring using a deep neural network. Sensors **20**(22), 6424 (2020)
29. Ries, J.D., et al.: Test-retest reliability and minimal detectable change scores for the timed "up & go" test, the six-minute walk test, and gait speed in people with Alzheimer disease. Phys. Ther. **89**(6), 569–579 (2009)
30. Macchia, A., et al.: A meta-analysis of trials of pulmonary hypertension: a clinical condition looking for drugs and research methodology. Am. Heart J. **153**(6), 1037–1047 (2007)
31. Chan, W.L.S., Pin, T.W.: Reliability, validity and minimal detectable change of 2-minute walk test, 6-minute walk test and 10-meter walk test in frail older adults with dementia. Exp. Gerontol. **115**, 9–18 (2019)
32. Ohashi, H., et al.: Augmenting wearable sensor data with physical constraint for DNN-based human-action recognition. In: ICML 2017 Times Series Workshop, pp. 6–11 (2017)