Intercontinental Geoinformation Days

igd.mersin.edu.tr

Comparative analysis of pedestrian stride length estimation methods

Nimet Karagöz[*1], **Fatih Gülgen** [1]

[1]Yildiz Technical University, Faculty of Civil Engineering, Department of Geomatics Engineering, Istanbul, Turkey

Keywords
Pedestrian navigation
Stride length estimation
Microelectromechanical system
Inertial sensors

ABSTRACT

The stride length estimation is a crucial step used in indoor and outdoor pedestrian navigation. The accuracy of the navigation process depends on how accurately the average stride length is calculated. The stride length estimation methods use some parameters such as step frequency, acceleration, and pedestrian height. These parameters are applied to different datasets containing various movements of pedestrians, such as running and walking. However, the limited datasets used in academic studies preclude scientific comparability in the literature. This study compares ten stride length estimation methods using the open-source datasets created by Wang and analyzes their accuracy. The case results show that Weinberg's approach was quite successful for navigation dynamics.

1. Introduction

In recent years, pedestrian navigation has gained popularity with the increase in the population living in complex and big cities and constructing substantial complex structures with developing engineering technologies (Zhang et al. 2018; Walchko 2002). It is sufficient for the accuracies to be in the order of kilometers for widely used vehicle navigation; the accuracy decreases to the level of meters for pedestrian navigation (Karimi, 2015). The fact that the designed pedestrian navigation applications have accuracy at the meter level is crucial for the pedestrians who do not have high mapping skills to follow the direction (May, 2003). In terms of simplicity and ease of use, virtual reality and augmented reality technologies are used in pedestrian navigation applications so that pedestrians can find their way easier with the help of visual and auditory tools (Dias et al., 2015). Global Navigation Satellite Systems (GNSS) are sufficient today, outdoors, in open areas to ensure enough accuracy. GNSS alone is insufficient in indoor or outdoor areas but areas surrounded by trees or high-rise buildings. For example, inertial measurement unit (IMU) sensors working with GNSS affect the accuracy positively (Kim et al., 2004; Kang et al., 2018). In addition, algorithms such as Kalman filter, extended Kalman filter, artificial intelligence are used in indoor pedestrian navigation to increase accuracy (Ladetto et al., 2001).

Pedestrian stride length estimation (SLE) accuracy, which is one of the primary stages of pedestrian navigation, has critical importance not only in the field of navigation but also in many fields such as medicine, the military, the study of human behavior, and sports (Ladetto et al., 2002; Rampp et al., 2014; Rasouli et al., 2017; Díez et al., 2018; Zeng et al., 2018). Studies in each area need to meet different expectations. In this context, there are various studies in which step lengths are for pedestrians such as running, fastly, or slowly walking (Shin et al., 2007; Martinelli et al., 2017). They use many technologies such as cameras, GNSS, IMU, and microelectromechanical system (MEMS) sensors in smartphones for stride length (SL) calculation (Kang et al., 2018; Wang et al., 2019).

On the other hand, since the datasets used in the studies were not open source and were not produced to a certain standard in terms of pedestrian behavior, technologies, and accuracy, SL calculation methods could not be adequately compared and analyzed (Ho et al., 2016; Xing et al., 2017). Wang et al. (2019) used an open-source dataset containing different pedestrian behaviors (Wang et al., 2019). This study compared the results obtained using ten other SL calculation methods.

* **Corresponding Author**

*(nmtkrgz@gmail.com) ORCID ID 0000 – 0002 – 6563 – 8393
(fgulgen@yildiz.edu.tr) ORCID ID 0000 – 0002 – 8754 – 9017

Cite this study

Karagöz N & Gülgen F (2021). Comparative analysis of pedestrian stride length methods. 3rd Intercontinental Geoinformation Days (IGD), 74-77, Mersin, Turkey

2. Method

2.1. Dataset and data preprocessing

The data collected with the Huawei Mate 9 smartphone with an octa-core 2.4 GHz processor includes sensor data in a 3D accelerometer, gyroscope, and magnetometer. The data collection frequency of the sensors is 100 Hz. The data includes step number, step length, total distance traveled, and time. The pedestrians are a total of five people, two women and three men. Their weight is between 45-80 kg, their age is between 23-32, and their height is 152-196 cm. Pedestrians carried the smartphone in their right hand at chest level with the screen parallel to the ground. Office, shopping mall, metro station, underground parking lot, street and pedestrian path are used as spaces. Running, walking, jumping, and taking the elevator were selected as pedestrian behaviors. An average of 122 pieces of data was recorded at each step. Less than 200 data was recorded in 99% of the steps.

Before applying the SLE methods, necessary unit transformations in the datasets were made. The effect of gravitational acceleration on the acceleration data is eliminated with the help of the rotation matrix calculated by using the accelerometer and magnetometer data recorded during the stance phase. The first two steps were omitted from all datasets to avoid degradation of data quality. One of the 30 datasets in total was excluded from the scope of the study due to missing data. As one dataset was used as a reference, analyzes of ten methods were performed on the remaining 28 datasets.

2.2. Stride length estimation methods and experiment

Ten SLE methods were evaluated in this study (Table 1). Data such as vertical acceleration, average acceleration, constants, and step frequency were used as parameters in the methods. The methods were implemented using Matlab 2020b software, where matrix calculations such as transformation matrix can be written quickly.

In the software, the time values given in the epoch are expressed in seconds to be compatible with the acceleration data. One of the datasets was selected, and the first data, including the pedestrian stance phase, was accepted as a reference. The smartphone's rotation in the pedestrian's hand was calculated from the acceleration data with the reference. A transformation matrix was generated from the obtained rotation. Each dataset was evaluated using this transformation matrix. The unknown parameters in each method were calculated with the selected reference data. The unknowns were placed in the formula, and the step lengths were calculated for the remaining datasets.

The accuracy of the SL's was calculated by assuming the SL measured by the IMU in each dataset as actual values. Equation 1-3 represents the relative error rate of SL and total walking distance and Root Mean Square Error (RMSE) of SL, respectively.

$$Relative\ Error_{SLE} = \frac{1}{N} \times \sum_{i=1}^{N} \left(\frac{|SL_e^i - SL_t^i|}{SL_t^i} \times 100 \right) \quad (1)$$

$$Relative\ Error_{WD} = \frac{|\sum_{i=1}^{N} SL_e^i - \sum_{i=1}^{N} SL_i^t|}{\sum_{i=1}^{N} SL_t^i} \times 100 \quad (2)$$

$$RMSE_{SLE} = \sqrt{\frac{\sum_{i=1}^{N} (SL_e^i - SL_t^i)^2}{N}} \quad (3)$$

To calculate the relative error of the i-th SL, the difference of the calculated stride length (SL_e^i) from the actual stride length (SL_t^i) is calculated, and it is divided by the actual SL, and it must be multiplied by 100, and the result must be divided by the total stride length (N) in the dataset. Similarly, the relative error of the total walking distance is obtained by subtracting the sum of the actual SL's from the sum of the calculated SL's, dividing the result by the total actual SL, and multiplying by 100. RMSE is obtained by dividing the difference of the calculated step lengths from the actual step lengths by the number of steps and taking the square root of the result.

3. Results

Estimated step lengths according to the selected ten different step length methods; (1) When compared with the median value of the actual SL, it was seen that the Weinberg (2002) method had the closest values to the actual value in 11 of 28 datasets. It was the most accurate and sensitive method with 0.001 m from the actual value in one of the datasets. Tian et al. (2015) and Bylemans et al. (2009) results have been followed by Weinberg (2002); the methods that most deviate from the actual median are Ladetto (2000), Zeng (2018), Mikov (2013), and Alvarez (2008).

(2) When the RMSE was analyzed, the standard deviations of Zeng and Ladetto were found to be the smallest, with 0.019 m. Guo, Weinberg, and Bylemans are the best methods after Zeng and Ladetto, respectively. Weinberg's standard deviation was found to be the best in 18 out of 28 data sets. On the other hand, in datasets with more steps, Kim and Ladetto have better standard deviations. (3) It was observed that the relative SL error was the least in Weinberg's method in 16 data sets. It has been determined that Weinberg's method has the best mean relative error among other methods and the slightest error scatter. When the data sets are examined one by one, and the total is analyzed, Mikov's method gave the most error. Considering the absolute and relative error for the total travel distance, it was determined that Mikov's scattering was high, but on the contrary, it had the slightest error in some datasets. The Weinberg method gave better results than the relatively new methods when the absolute and relative total traveled distance errors were examined. Zeng and Alvarez do not give the most successful results in any of the datasets. Successful results were obtained from Kim, Mikov, and Bylemans in datasets which are containing more steps.

Table 1. Information of selected SLE methods

Models Source	SLE Methods	Parameters
Weinberg, 2002	$K \times \sqrt[4]{a_{vmax} - a_{vmin}}$	tunable constant (K), maximum and minimum vertical acceleration (a_{vmax}, a_{vmin})
Ladetto, 2000	$\alpha \cdot f + \beta \cdot v + \gamma$	coefficients (α, β, γ), walking frequency (f), the variance of acceleration (v)
Kim et al., 2004	$K \times \sqrt[3]{\sum_{i=1}^{N} \frac{\lvert a_i \rvert}{N}}$	coefficient (K), mean acceleration (a_i), number of the sample (N)
Scarlett, 2007	$K \times \frac{\sum_{i=1}^{N} \frac{\lvert a_i \rvert}{N} - a_{min}}{a_{max} - a_{min}}$	coefficient (K), mean acceleration (a_i), maximum and minimum vertical acceleration (a_{max}, a_{min})
Alvarez et al., 2008	$K_1 \cdot F + K_2$	tunable constants (K_1, K_2), step frequency (F)
Bylemans et al., 2009	$0.1 \sqrt[2.7]{a_{avg,abs} \sqrt{K \sqrt{\frac{F}{a_v}}}}$	tunable constant (K), step frequency (F), average absolute vertical acceleration ($a_{avg,abs}$), difference between the maximum and minimum vertical acceleration (a_v)
Mikov et al., 2013	$\frac{K}{F} \sqrt[4]{a_v}$	tunable constant (K), step frequency (F), difference between the maximum and minimum vertical acceleration (a_v)
Guo et al., 2016	$K_1 \sqrt[3]{a_{avg}} + K_2$	tunable constants (K_1, K_2), average absolute acceleration (a_{avg})
Tian et al., 2015	$K \times h \times \sqrt{F}$	coefficient (K), step frequency (F), pedestrian height (h)
Zeng et al., 2018	$\frac{\sqrt{K_2^2 - 4 \times K_1 \times (K_3 - F)} - K_2}{2 \times K_1}$	coefficients (K_1, K_2, K_3), step frequency (F)

4. Discussion

In the study, 28 different databases consisting of MEMS sensor data, formed from five users moving in six different environments at different speeds and patterns, were considered whole, and results were obtained. A transformation matrix was generated by looking at the first magnetometer and accelerometer records of a dataset. Likewise, while calculating the parameters in the methods, data from a single dataset were used. Median, standard deviation, absolute, and relative error were calculated from the obtained step lengths. It was observed that eight methods gave approximately the same results. The SL was calculated with an average error of 13.06%. However, Weinberg's method was the best method with an error of 7.44% and 5.61% in SL and total walking distance, respectively, while Mikov's method was the worst method with 54.34% and 44.63%. It is thought that more accurate results can be obtained if the acceleration rotation is calculated according to the median of the records for each dataset, rather than the transformation matrix. However, for a real-time pedestrian navigation system, this calculation is trivial because not all steps can be obtained. However, it is thought that the results can be improved if a separate parameter estimation is made for each method in each dataset. If the data are grouped according to the number of steps they contain, users, or walking environments and the parameters are calculated according to these groups; it is predicted that more accurate results can be obtained. For example, since the user's height information is not available, in the Tian method, the height is considered a constant and calculated by optimization. Changing the optimization method or choosing a different starting value has affected the accuracy of this method. It was concluded that Weinberg's method should be the first choice for many navigation applications, considering its accuracy and sensitivity, in the absence of sufficient attribute information about the database.

5. Conclusion

One of the essential stages of pedestrian navigation is SLE. Ten selected SLE methods were studied. Methods were applied to the open-source datasets shared by Wang et al.

Future research will be essential to produce a variety of open-source datasets that record data from more users, include more diverse human behaviors, and contain fewer and more steps. By training these datasets, more efficient results can be obtained with artificial intelligence. In this way, more vital information can be provided in online applications by correcting the previous steps. Designing the analyzes made in the study as a desktop application and enriching it with artificial intelligence, automatically calculating step lengths according to the inputs of the dataset, and performing accuracy analysis for more various SLE methods will be the subject of future research.

References

Alvarez, D., González, R. C., López, A., & Alvarez, J. C. (2008). Comparison of step length estimators from wearable accelerometer devices. In Encyclopedia of Healthcare Information Systems (pp. 244-250). IGI Global.

Bylemans, I., Weyn, M., & Klepal, M. (2009, October). Mobile phone-based displacement estimation for opportunistic localisation systems. In 2009 Third International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies (pp. 113-118). IEEE.

Dias, M. B., Teves, E. A., Zimmerman, G. J., Gedawy, H. K., Belousov, S. M., & Dias, M. B. (2015). Indoor navigation challenges for visually impaired people. Indoor Wayfinding and Navigation, 141-164.

Díez, L. E., Bahillo, A., Otegui, J., & Otim, T. (2018). Step length estimation methods based on inertial sensors: A review. IEEE Sensors Journal, 18(17), 6908-6926.

Guo, Y., Sun, Y., Luo, H., & Guizani, N. (2016). Accurate indoor localization based on crowd sensing. Wireless Communications and Mobile Computing, 16(17), 2852-2868.

Ho, N. H., Truong, P. H., & Jeong, G. M. (2016). Step-detection and adaptive step-length estimation for pedestrian dead-reckoning at various walking speeds using a smartphone. Sensors, 16(9), 1423.

Kang, J., Lee, J., & Eom, D. S. (2018). Smartphone-based traveled distance estimation using individual walking patterns for indoor localization. Sensors, 18(9), 3149.

Karimi, H. A. (Ed.). (2015). Indoor wayfinding and navigation. CRC Press.

Kim, J. W., Jang, H. J., Hwang, D. H., & Park, C. (2004). A step, stride and heading determination for the pedestrian navigation system. Journal of Global Positioning Systems, 3(1-2), 273-279.

Ladetto, Q. (2000, September). On foot navigation: continuous step calibration using both complementary recursive prediction and adaptive Kalman filtering. In Proceedings of the 13th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GPS 2000) (pp. 1735-1740).

Ladetto, Q., Gabaglio, V., & Merminod, B. (2001). Two Different Approaches for Augmented GPS Pedestrian Navigation.

Ladetto, Q., Van Seeters, J., Sokolowski, S., Sagan, Z., & Merminod, B. (2002). Digital magnetic compass and gyroscope for dismounted soldier position & navigation. In Military Capabilities enabled by Advances in Navigation Sensors, Sensors & Electronics Technology Panel, NATO-RTO meetings, Istanbul, Turkey (No. CONF).

Martinelli, A., Gao, H., Groves, P. D., & Morosi, S. (2017). Probabilistic context-aware step length estimation for pedestrian dead reckoning. IEEE Sensors Journal, 18(4), 1600-1611.

May, A. J., Ross, T., Bayer, S. H., & Tarkiainen, M. J. (2003). Pedestrian navigation aids: information requirements and design implications. Personal and Ubiquitous Computing, 7(6), 331-338.

Mikov, A., Moschevikin, A., Fedorov, A., & Sikora, A. (2013, October). A localization system using inertial measurement units from wireless commercial hand-held devices. In International Conference on Indoor Positioning and Indoor Navigation (pp. 1-7). IEEE.

Rampp, A., Barth, J., Schülein, S., Gaßmann, K. G., Klucken, J., & Eskofier, B. M. (2014). Inertial sensor-based stride parameter calculation from gait sequences in geriatric patients. IEEE transactions on biomedical engineering, 62(4), 1089-1097.

Rasouli, A., Kotseruba, I., & Tsotsos, J. K. (2017). Are they going to cross? A benchmark dataset and baseline for pedestrian crosswalk behavior. In Proceedings of the IEEE International Conference on Computer Vision Workshops (pp. 206-213).

Scarlett, J. (2007). Enhancing the performance of pedometers using a single accelerometer. Application Note, Analog Devices, (AN-900).

Shin, S. H., Park, C. G., Kim, J. W., Hong, H. S., & Lee, J. M. (2007, February). Adaptive step length estimation algorithm using low-cost MEMS inertial sensors. In 2007 IEEE sensors applications symposium (pp. 1-5). IEEE.

Tian, Q., Salcic, Z., Kevin, I., Wang, K., & Pan, Y. (2015). A multi-mode dead reckoning system for pedestrian tracking using smartphones. IEEE Sensors Journal, 16(7), 2079-2093.

Xing, H., Li, J., Hou, B., Zhang, Y., & Guo, M. (2017). Pedestrian stride length estimation from IMU measurements and ANN based algorithm. Journal of Sensors, 2017.

Walchko, K. J. (2002). Low cost inertial navigation: Learning to integrate noise and find your way (Doctoral dissertation, University of Florida).

Wang, Q., Ye, L., Luo, H., Men, A., Zhao, F., & Huang, Y. (2019). Pedestrian stride-length estimation based on LSTM and denoising autoencoders. Sensors, 19(4), 840.

Weinberg, H. (2002). Using the ADXL202 in pedometer and personal navigation applications. Analog Devices AN-602 application note, 2(2), 1-6.

Zeng, G., Cao, S., Liu, C., & Song, W. (2018). Experimental and modeling study on relation of pedestrian step length and frequency under different headways. Physica A: Statistical Mechanics and its Applications, 500, 237-248.

Zhang, M., Wen, Y., Chen, J., Yang, X., Gao, R., & Zhao, H. (2018). Pedestrian dead-reckoning indoor localization based on OS-ELM. IEEE Access, 6, 6116-6129.