Title
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Abstract. Wayfinding systems using inertial data recorded from a smartphone carried by the walker have great potential for increasing mobility independence of blind pedestrians. Pedestrian dead-reckoning (PDR) algorithms for localization require estimation of the step length of the walker. Prior work has shown that step length can be reliably predicted by processing the inertial data recorded by the smartphone with a simple machine learning algorithm. However, this prior work only considered sighted walkers, whose gait may be different from that of blind walkers using a long cane or a dog guide. In this work, we show that a step length estimation network trained on data from sighted walkers performs poorly when tested on blind walkers, and that retraining with data from blind walkers can dramatically increase the accuracy of step length prediction.

1 Introduction

Independent wayfinding can be challenging for people who are blind. While GPS localization can be very helpful in outdoor environments, GPS cannot be used inside buildings, and thus different mechanisms for localization and wayfinding need to be relied upon. In this work we focus on inertial sensing for localization. Inertial sensors (accelerometers and gyros) are contained in any standard smartphone. Data from these sensors can be used by pedestrian dead-reckoning (PDR) algorithms to estimate the user's location given a known starting point. One important advantage of inertial navigation is that it doesn't require an external infrastructure, as is the case, for example, for wayfinding systems based on Bluetooth Low Energy (BLE) beacons. Compared to vision-based systems, inertial sensing has the advantage that it does not require the user to hold the smartphone such that the camera gets a clear view of the environment. Users can conveniently keep their smartphone in their pocket, and be tracked by the system as they move around.

Standard PDR algorithms use inertial data to count the number of steps taken by the user, and to determine the walking direction. By multiplying the number of steps by each step's length, the distance traversed in a certain period of time can be determined. This approach, however, assumes that the length of each step be known in advance. This requires a prior calibration phase, during which the "natural" step length of the user is computed. However, even after calibration, it is quite possible that the user may not maintain a constant step length. For example, walkers may take shorter steps when they are unsure of where they are going, or when negotiating an obstacle. In these cases, the odometry system would make localization errors and consequently provide wrong directions.

In prior work [4], Elyasi et al. presented a machine learning algorithm to estimate the length of each step taken by a walker, based on the same inertial data that is used by the smartphone-based PDR algorithm. This algorithm, which employs an LSTM recurrent network, was originally tested on sighted walkers, and was shown to produce rather accurate results. In this contribution, we present a study in which tested a similar algorithm on 7 blind walkers (5 using a long cane and 2 using a dog guide). Note that the gait of a blind walker using a cane is typically different from that of a sighted walker, and it is also different from that of walkers using a dog guide. It is thus important that the step length prediction system be tested with data from walkers from the same communities the wayfinding is designed for.

2 State of the Art

Inertial-based wayfinding systems for blind travelers were described in [12, 1]. In particular, [1] proposed online estimation of step length in the context of Particle Filtering. Traditional methods for step length estimation were based, for example, on the relationship between the step length and the difference of max and min values of the vertical acceleration within the step [15]. Other methods used the magnitude of acceleration [7] or its local variance [9]. [3, 11] used a combination of the user's step frequency and height. More recent approaches are based on machine learning. For example [6] used stacked autoencoders to learn valuable features from accelerometer and gyro data through stacked autoencoders, while [16] used deep belief networks. StepNet [8] uses a combination of high-level features with a convolutional neural network (CNN)-based. Wand et al. [14], used a combination of LSTM and autoencoder model. Elyasi et al. fed data from accelerometer and gyro to an LSTM followed by a fully convolutional layer.

3 Methodology

Our goal was to verify whether the algorithm of [4], applied to inertial data from a smartphone carried by blind users, could produce reliable step length measurements for our blind participants. This algorithm proceeds as follows. First, the recorded time series of inertial data is segmented into "steps", defined as the interval of time between two consecutive heel strikes from opposite feet. Heel strikes where computed using the algorithm of [10]. Then, from the data within a step period, a step length is inferred using an LSTM-based algorithm. This network was trained using ground-truth data recorded from foot-mounted sensors (Xsens DOT IMU packages, each tied to either shoe using an elastic band). As well known [5], zero-velocity updates can be applied to data from foot-level sensors for precise dead-reckoning. We applied the ZUPT algorithm [5], along with HDR correction [2] to reduce gyro drift, to the data from the foot sensors to reconstruct the trajectory of the users' motion. From this, we computed the ground-truth length of each step, which was used in the loss function considered when training the step length measurement network from smartphone data. For more details, please refer to [4].

We recruited seven blind participants for this test (4 female, 3 male). Two participants (P1 and P7) used a dog guide, while the others used a long cane. The participants' ages raged from 53 to 76. Each participant walked with an iPhone 12, which was used to record inertial data. tucked in a pants pocket. In addition, they were equipped with the two foot sensors mentioned earlier. Each participant walked for 292 meters through the corridors of a building. While walking, they kept the data-collecting iPhone in their back pocket. The histogram of ground-truth recorded step lengths is shown in Fig. 1, together with the histogram of step lengths recorded in the experiment with sighted participants described in [4]

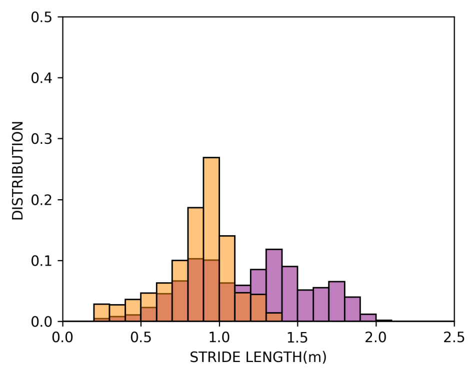


Fig. 1. Distribution of stride lengths for all blind participants in our study (orange bars), shown alongside the stride length distribution for the data set of sighted participants in [4] (purple bars).

We considered four different training modalities for training the LSTM algorithm of [4]:

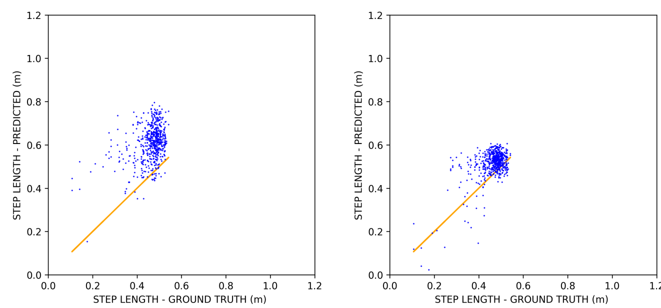
- *Train on Sighted (TS)*: In this modality, we used the original model of [4], which was trained on data from sighted walkers, and tested it on the data collected from all 7 blind participants.
- *Train in Community (TC)*: In this case, each walker using a long cane was tested with a system trained from all the 6 other walkers long cane users. Likewise, each walker with a dog guide was tested with a system trained on data from the other dog guide user.
- *Train on Blind (TB)*: Each blind participant was tested with a system trained on data from all other blind participants (regardless of whether they used a long cane or a dog guide).

– *Train on All (TA)*: Each blind participant was tested with a system trained on all sighted participants, as well as all other blind participants.

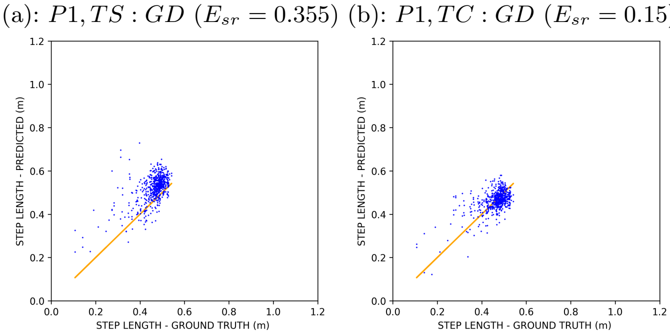
Note that *TC*, *TB* and *TA* use the "leave-one-person-out modality". In all cases, data from a certain walker was never used for training the network tested on that user.

4 Results

We processed the data recorded from the participants' iPhone to estimate each individual step length, then compared the results with the ground-truth step lengths from the foot-level sensors. Figs. 2 and 3 show examples of estimated step lengths plotted against their ground-truth values for different training modalities. In these plots, the red line represents the locus of zero error estimations.



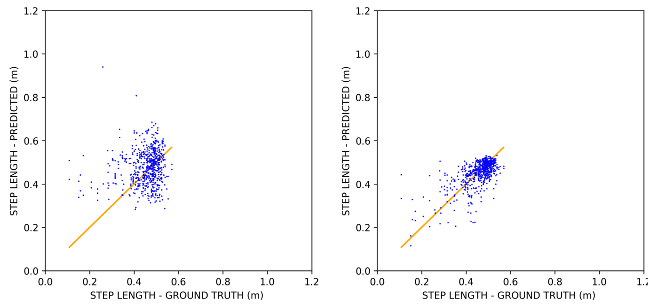
(a): $P1, TS : GD$ ($E_{sr} = 0.355$) (b): $P1, TC : GD$ ($E_{sr} = 0.15$)



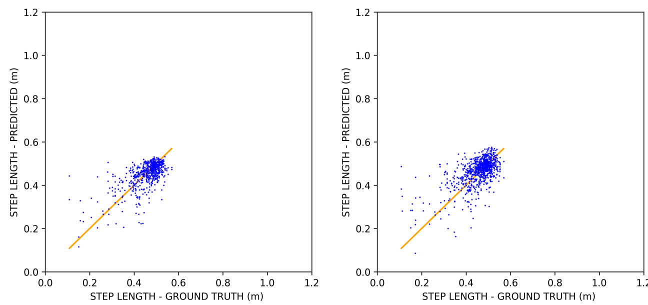
(c): $P1, TA : GD$ ($E_{sr} = 0.15$) (d): $P1, TB : GD$ ($E_{sr} = 0.09$)

Fig. 2. Examples of step length prediction for $P1$ (a dog guide user) for different Training/Test modalities, plotted against their ground truth values.

To quantify the step length errors (difference between estimated and ground truth values), we e used the error metrics defined in [4], which are summarized in the following.



(a): $P3, TS : LC$ ($E_{sr} = 0.19$) (b): $P3, TC : LC$ ($E_{sr} = 0.10$)



(c): $P3, TA : LC$ ($E_{sr} = 0.11$) (d): $P3, TB : LC$ ($E_{sr} = 0.11$)

Fig. 3. Examples of step length prediction for $P3$ (a long cane user) for different Training/Test modalities, plotted against their ground truth values.

- $E_d = \dfrac{|\sum_{i=1}^N l_i - \sum_{i=1}^N \hat{l}_i|}{\sum_{i=1}^N \hat{l}_i}$
- $E_s = \dfrac{1}{N}\displaystyle\sum_{i=1}^N |l_i - \hat{l}_i|$
- $E_{sr} = \dfrac{1}{N}\displaystyle\sum_{i=1}^N \dfrac{|l_i - \hat{l}_i|}{\hat{l}_i}$
- $R^2 = 1 - \dfrac{\text{RMSE}^2}{\sigma^2}$, where $\text{RMSE} = \sqrt{\dfrac{\sum_{i=1}^N (l_i - \hat{l}_i)^2}{N}}$ and σ^2 is the variance of the set of ground truth step lengths $\{\hat{l}_i\}$.

In these formulas, $\hat{l}_i$ represents the ground truth length of the i-th step in the test set for a certain participant, while l_i is the step length predicted by the LSTM system. E_d is the relative distance error, which is an appropriate measure for long paths where step-to-step error fluctuations tend to cancel out. E_s represents the average absolute error at each step. E_{sr} normalizes errors with the ground truth step length. R^2 (often called "coefficient of determination") is a number that is equal to 1 only in case of zero error, and is less than 1 otherwise. A negative R^2 means that the prediction $\{l_i\}$ gives a worse RMSE than using a constant value equal to the average step length.

The average errors are reported in Tab. 1 for the participants using a long cane, and in Tab. 2 for the participants using a dog guide.

Table 1: Error metrics computed for all Training/Test modalities for long cane users.

	E_d	E_s (m)	E_{sr}	R^2
TS	0.14 ± 0.10	0.09 ± 0.03	0.29 ± 0.11	-0.95 ± 0.96
TC	0.02 ± 0.01	0.05 ± 0.01	0.14 ± 0.03	0.48 ± 0.08
TB	0.03 ± 0.02	0.05 ± 0.01	0.14 ± 0.03	0.43 ± 0.12
TA	0.02 ± 0.01	0.05 ± 0.01	0.15 ± 0.03	0.44 ± 0.03

Table 2: Error metrics computed for all Training/Test modalities for guide dog users.

	E_d	E_s (m)	E_{sr}	R^2
TS	0.19 ± 0.18	0.14 ± 0.01	0.353 ± 0.03	-3.79 ± 4.64
TC	0.18 ± 0.10	0.11 ± 0.07	0.23 ± 0.11	-0.75 ± 0.03
TB	0.07 ± 0.10	0.07 ± 0.04	0.15 ± 0.08	0.25 ± 0.07
TA	0.07 ± 0.08	0.07 ± 0.01	0.17 ± 0.02	-0.22 ± 0.94

5 Discussion

The main goal of this test was to evaluate whether a step length measurement system trained on sighted walkers would work well for blind walkers using a long cane or a dog guide, or retraining was in order. We hypothesized that the gait of blind walkers could be different from that of sighted walkers, motivating our research question. The results presented in Tabs. 1 and 2 show that the largest errors were observed when the network was trained with sighted walkers, while better values were obtained when data from blind walkers were included in the training set. Indeed, when the system was trained solely with data from sighted users, the value of R^2 was negative for both long cane and dog guide users, meaning that using a constant value equal to the average step length for each user would give a lower mean square error than using the prediction from the system. This can also be seen qualitatively in Fig. 2 (a) and Fig. 3 (a), which show a large spread of step length predictions for the same ground-truth value.

We note that for dog guide users, the TC modality resulted in a negative value for R^2. This is likely because in this case the system was only trained with data from only one other user (since there were only two dog guide users in our set of participants). The best results are obtained with the *TB* modality, where for each participant, data from all other blind participants was considered.

6 Conclusions

Step length estimation is a critical component of a PDR system used for localization and wayfinding in indoor environments. Prior work showed the feasibility of recurrent neural networks for step length estimation from inertial data. However, this algorithm was only tested with sighted walkers. Our study has shown that, with proper training, a similar architecture can be used successfully for blind walkers, and can thus be integrated in a complete inertial-based wayfinding system. In future work, we will integrate a properly trained step length measurement system in the indoor wayfinding and backtracking app described in [13].

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