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Wearable Sensor-Based Step Length Estimation During Overground Locomotion Using a Deep Convolutional Neural Network

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***Abstract*— Step length is a critical gait parameter that allows a quantitative assessment of gait asymmetry. Gait asymmetry can lead to many potential health threats such as joint degeneration, difficult balance control, and gait inefficiency. Therefore, accurate step length estimation is essential to understand gait asymmetry and provide appropriate clinical interventions or gait training programs. The conventional method for step length measurement relies on using foot-mounted inertial measurement units (IMUs). However, this may not be suitable for real-world applications due to sensor signal drift and the potential obtrusiveness of using distal sensors. To overcome this challenge, we propose a deep convolutional neural network-based step length estimation using only proximal wearable sensors (hip goniometer, trunk IMU, and thigh IMU) capable of generalizing to various walking speeds. To evaluate this approach, we utilized treadmill data collected from sixteen able-bodied subjects at different walking speeds. We tested our optimized model on the overground walking data. Our CNN model estimated the step length with an average mean absolute error of 2.89 $\pm$ 0.89 cm across all subjects and walking speeds. Since wearable sensors and CNN models are easily deployable in real-time, our study findings can provide personalized real-time step length monitoring in wearable assistive devices and gait training programs.**

***Index Terms*— Step Length Estimation, Wearable Sensor, Convolutional Neural Network, Gait Analysis**

I. Introduction

Gait asymmetry, irregular behaviors of bilateral limbs during walking, can lead to many potential risks to our health. Persisting asymmetric gait could repetitively apply higher forces to a particular leg and cause uneven load distributions, which can lead to degenerative joint diseases, risks of falling, and inefficient energy expenditure [1]–[3]. To prevent potential health damages, it is essential to identify the existence of gait asymmetry. Step length, in particular, is a very important spatial gait parameter for gait asymmetry assessment. Individuals with asymmetric gait typically show high variability in step length [4]. Measuring the variability in step length allows us to understand the walking mechanism and underlying impairment [5], [6], and therefore informs us if preventative clinical interventions or rehabilitation efforts need to be sought. Restoration of step length symmetry can greatly contribute to the reduction in the metabolic cost of walking. This has important implications in designing rehabilitation programs as well as innovative healthcare technology such as assistive wearable devices because lower-limb wearable devices are also challenged by the motivation to minimize the metabolic cost of walking [7]–[9]. To allow such applications, it is critical to enable accurate and efficient step length estimation.

A common method is to use a foot-mounted inertial measurement unit (IMU) [10]. Because IMU cannot directly measure step length, step length needs to be estimated by computing double integration of the acceleration data from IMU. However, this approach is very sensitive to the accumulation of drift. To alleviate this problem, a zero velocity update algorithm (ZUPT) is typically used to reset the integrated velocity to zero whenever the foot is stationary. As ZUPT works according to the foot movement, IMU placement on the foot is considered necessary for step length estimation. However, IMU placement in a distal area creates the need to have additional wires, which can potentially hinder the user's movement. To minimize such obtrusiveness, a more viable solution is to place the IMU on proximal body segments such as the trunk or thigh. This approach can also allow wearable devices that do not have distal interfaces, such as hip exoskeletons, to estimate step length.

Nevertheless, IMU and ZUPT still have a huge drawback because they do not work properly in dynamically changing walking environments [11]. A possible solution to mitigate the limitations is to incorporate machine learning-based (ML) step length estimation. Among different ML approaches, a convolutional neural network (CNN) has shown very promising results due to its success in feature learning and often brings performance gain compared to hand-crafted feature extraction [12]. Sharifi Renani *et al.* showed that a CNN model can help overcome the sensor placement dependency for IMU-based spatial-temporal gait parameter estimation [13], and Hannink *et al.* demonstrated that their CNN models performed better than the IMU-based double integration method in geriatric gait analysis [14].

While these studies prove the feasibility of implementing CNN for gait parameter estimation, they do not focus on demonstrating a CNN model's generalizability to different speeds. Therefore, we propose a deep CNN-based step length estimation method that is capable of adapting to dynamic speeds, using proximal wearable sensors. This proposed method will help translate step length monitoring to more realistic settings since our CNN model eliminates the obtrusiveness of distal sensors as well as potential cumulative

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errors caused by IMU integration.

Our hypothesis is that by using the treadmill data collected at different speeds, the CNN model can learn to adapt to changing walking environments. Utilizing a treadmill allows us to simplify the experimental procedures and achieve great efficiency because treadmills can be easily and safely controlled to provide a variety of possible overground walking speeds. To test our hypothesis, we evaluated the performance of our model using the overground data, which represents realistic free-walking conditions. We also compared our CNN model with a mathematical estimation method, which estimates step length by calculating the average step length across all overground walking speeds for each subject. The main objective of our study is to validate the feasibility of implementing a deep CNN model to accurately estimate step length in dynamic conditions. Our study findings can be used to provide customized real-time step length monitoring in assistive wearable devices and gait rehabilitation programs, and therefore improve the step length estimation to be more applicable in real-world settings.

II. Methods

A. Step Length Dataset

Our study utilized a publicly available open-source dataset collected by our group [15], in which sixteen healthy young individuals (age of 22.13 $\pm$ 3.92 years, height of 1.70 $\pm$ 0.07 m, and body mass of 68.38 $\pm$ 11.84 kg) were asked to walk on a treadmill and overground. The treadmill data were recorded at different speeds ranging from 0.5 m/s to 2.05 m/s with increments of 0.05 m/s, and each speed was held for 30 seconds. For the overground data, subjects were asked to walk on a ground terrain at their three different preferred walking speeds: slow, normal, and fast. Within the overground trial data, only the steady-state walking data were used in this study. Both treadmill and overground data were collected with a 36-camera Vicon motion capture system (Oxford Metric, Oxford, UK). The 200 Hz motion capture marker data were filtered with a zero-lag low-pass filter with a cutoff frequency of 6 Hz.

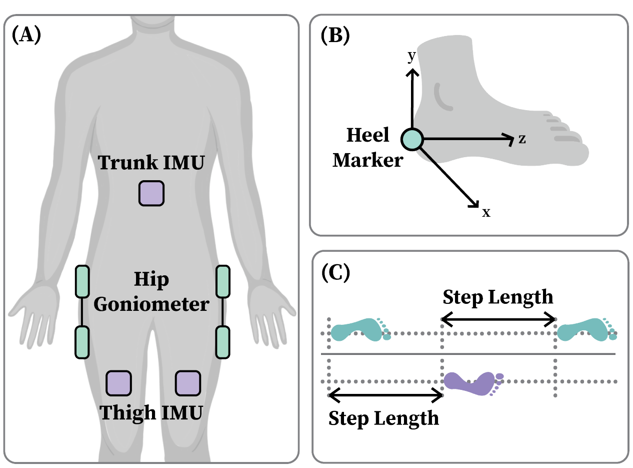

Fig. 1. (A) Locations and types of simulated bilateral sensors. (B) Placement and x, y, z axes definition of the Vicon heel marker. (C) Illustration of the analyzed spatial gait parameter: step length.

Conventionally used mechanical sensors for wearable robotics are the joint encoder and the inertial measurement unit (IMU). To simulate these sensors for our dataset, we used the open-source modeling software, OpenSim V4.1. We used the Inverse Kinematics Tool to generate the users' joint kinematics data representing the hip goniometer (GON) along the sagittal plane. Additionally, we utilized motion capture marker position to determine the 6-axis IMU data (local acceleration and angular velocity of corresponding limb segment). During this sensor data generation, we generated two GON for bilateral hip joints and three IMUs for each limb segment (trunk and thigh) (Fig. 1A) to use for training and testing our CNN model. Using this sensor fusion approach, comprehensive information about the user's gait patterns can be provided to the CNN model [16].

Each step event was defined at heel strike, which was detected at 0% of the gait phase of each foot. When segmenting steps from the treadmill data, we discarded steps that were performed at speeds below 0.5 m/s during treadmill starting and stopping. From all sixteen subjects, a total of 29867 steps were obtained from the treadmill data, and 5846 steps from the overground data were obtained. The average step length of the treadmill and overground data was 60.85 $\pm$ 3.21 cm and 62.23 $\pm$ 5.59 cm, respectively. These values represent the mean $\pm$ standard deviation across sixteen subjects. The ground truth for step length was determined using the heel marker locations, extracted from Vicon motion capture system. Step length was defined as the distance between z coordinates of the left and right heel markers at each step event (Fig. 1B and C).

B. Model Optimization

We developed a user-dependent model using data that was specific to the subject. Our model was trained offline for a maximum of 1000 iterations with a batch size of 64. To avoid overfitting of the user-dependent models, early stopping criteria was used to terminate training if the validation loss did not continue to decrease [17]. Within user-specific data, 5-fold validation was performed to better evaluate the performance of the model.

Our deep CNN architecture consists of four 1-dimensional convolutional layers, a 1-dimensional average pooling layer, and two fully connected layers (Fig. 2). For the first two convolutional layers, the channel dimensions increase because scaling up dimensions is effective for capturing more fine features [18]. Each convolutional layer is followed by batch normalization and rectified linear unit (ReLU) activation function to optimize training. The 1-dimensional pooling layer is added before the fully connected layers to summarize and down-sample the feature maps by taking the average in non-overlapping windows [12]. The output of the pooling layer is flattened to a fully connected layer. After the first fully connected layer, the number of hidden nodes is decreased by half for model compression. Lastly, the final

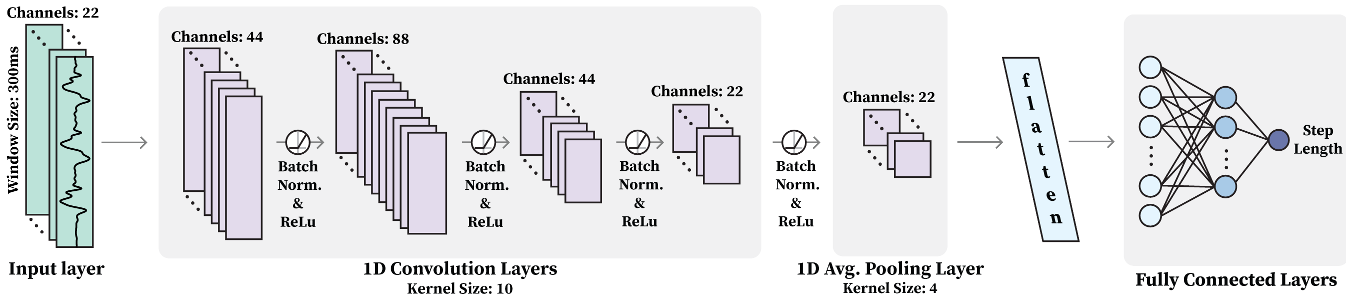

Fig. 2. Convolutional Neural Network-based step length estimator. Raw sensor data generated by IMU simulation using OpenSim is directly fed to the input layer. Each hidden node of the fully connected layers is followed by the ReLU activation function. The output node produces step length estimation.

layer transforms the last hidden layer to a single output for step length prediction.

The input sequence length was fixed at 300ms, which was selected to fit the minimum step time between two consecutive heel strikes. This prevented any overlap between data from consecutive steps, meaning there was no signal information "leakage" from the previous steps. The mean squared error (MSE) was selected for the loss function, and Adam with decoupled weight decay (AdamW) with a learning rate of 0.001 was used for optimization [19]. Loshchilov and Hutter proposed that AdamW is much better at generalization than Adam, and AdamW performs especially well when combined with a learning rate schedule. Hence, during training, AdamW was applied with a "plateau" learning scheduler which reduced the learning rate when the validation loss stopped decreasing. The network was implemented and trained using PyTorch library.

C. Model Validation

Using the overground data, we tested our offline user-dependent model. The overground data was specific to the same subject who provided the training data. Since the overground data covers a wide range of possible natural walking speeds, it allows us to validate if the model is capable of generalizing to different situations where the user is accelerating or decelerating. To better evaluate the performance of the CNN model, the mathematical estimation approach was implemented as a baseline model to draw comparisons between them. The baseline model defines its step length estimation by calculating the average step length across all overground walking speeds for each subject. The mean absolute error (MAE) and the mean absolute percentage error (MAPE) were computed between the ground truth and the prediction from the two models to evaluate the overall estimation performance. Additionally, we have conducted a statistical analysis on our model performance with an alpha value set to 0.05. A two-way repeated measures analysis of variance (ANOVA) was used to find significant differences across conditions (MATLAB R2020b, Mathworks). Lastly, *post hoc* multiple comparisons with a Bonferroni correction were used to compute a pairwise differences.

TABLE I
STEP LENGTH ESTIMATION PERFORMANCE OF THE TWO PROPOSED MODELS ACROSS ALL SUBJECTS AND SPEEDS.

Error Measure	Baseline	CNN
MAE ± STD (cm)[1]	6.59 ± 1.63	2.89 ± 0.89
MAPE ± STD (%)[2]	11.17 ± 2.18	4.70 ± 1.18

[1] Mean absolute error ± standard deviation
[2] Mean absolute percentage error ± standard deviation

III. RESULTS

Across all subjects and speeds, the CNN model on average reduced the estimation error rate relative to the baseline model by 52.24 ± 20.01% ($p < 0.05$) (Table 1).

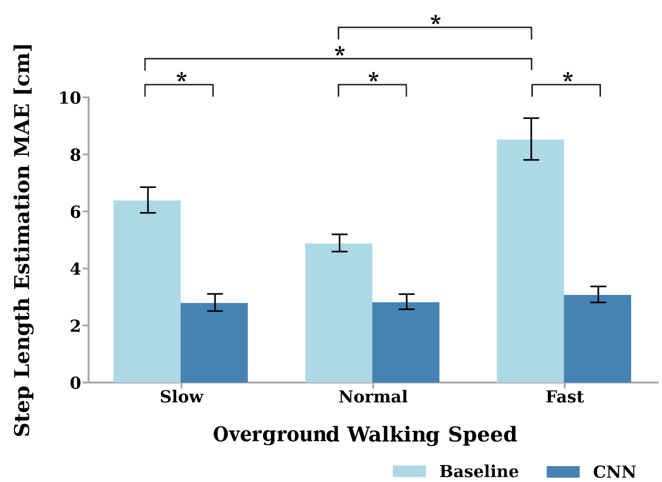

Fig. 3. MAE comparison between the baseline model and the CNN model at different preferred speeds across all subjects. The error bars represent ± 1 standard error of the mean (SEM) and asterisks indicate statistical significance ($p < 0.05$).

The CNN model resulted in an average MAE of 2.79 ± 1.20cm, 2.81 ± 1.07 cm, 3.07 ± 1.12 cm, whereas the baseline model resulted in an average MAE of 6.38 ± 1.80cm, 4.87 ± 1.21cm, 8.52 ± 2.93cm at slow, normal, and fast walking speed, respectively (Fig. 3). The CNN model on average reduced the MAE compared to the baseline model by 54.15 ± 19.23%, 41.01 ± 19.97%, and 61.59 ± 14.69%

at slow, normal, and fast walking speed, respectively ($p < 0.05$). The baseline model performance was worse at fast walking compared to slow and normal walking ($p < 0.05$). There were no significant statistical differences between the CNN model performances across three walking speeds.

IV. Discussion and Conclusion

Our study introduced and validated a novel CNN model, able to estimate step length within 2.89 $\pm$ 0.89 cm using proximal wearable sensors during overground walking at varying speeds. Not only did the CNN model outperform the baseline estimate by 52%, but it also generalized well across all tested walking speeds. This result corresponds to our hypothesis that a CNN-based approach can successfully adapt to dynamic walking speeds.

A literature study by Sharifi Renani *et al.* used a similar approach to our study and presented relevant results [13]. Sharifi Renani *et al.* showed the average normalized absolute percentage error (NAPE) of all sensor combinations for step length estimation was 8.0 $\pm$ 4.32 %. The NAPE is defined as the absolute error divided by the mean of the labeled test data. Moreover, the study reported that the NAPE was higher at fast walking (17.6%), compared to slow and normal walking (15.8%) across 12 different spatial-temporal gait parameter estimations. Although we cannot make a direct comparison due to using different sensors and a different error measurement from their study, our CNN-based model accurately estimated step length with an average MAPE of 4.70 $\pm$ 1.18% (Table 1) which overcame the challenge of making estimation in varying walking speeds.

There were several limitations to this study that should be considered: 1) The CNN model was trained on a user-specific basis. Even though a user-dependent model can provide better "customized" estimation than a user-independent model, the user-dependent approach has limitations in generalizing to a novel user, and therefore may not be optimal for real-world applications. To mitigate this, a transfer learning approach can be explored, where the baseline model can adapt to a novel user using additional data inherent to the user's gait patterns. 2) Since the model was trained and tested offline, our study did not explore if the model is capable of performing accurate real-time step length estimation. 3) Our study only investigated step length estimation during steady-state walking and did not consider situations where the user might be changing directions.

In future work, we want to address the feasibility of using a user-independent CNN model with turning phases for step length estimation. Online testing should also be performed to better evaluate its real-life applicability. This will expand the ability of the CNN model to handle more realistic human movements. For this study, we chose a simple mathematical approach as the baseline to compare our model performance across different walking speeds. Future work can use a more robust analytical approach (e.g., foot-mounted IMU-based estimation) as the baseline to fully evaluate the advantage of leveraging deep learning for step length estimation. These improvements will provide great potential for enabling personalized real-time step length monitoring in wearable assistive devices and rehabilitation programs.

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