Human Gait Database for Normal Walk Collected by Smart Phone Accelerometer

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Abstract
Gait recognition is the characterization of unique biometric patterns associated with each individual which can be utilized to identify a person without direct contact. A public gait database with a relatively large number of subjects can provide a great opportunity for future studies to build and validate gait authentication models. The goal of this study is to introduce a comprehensive gait database of 93 human subjects who walked between two endpoints (320 meters) during two different sessions and record their gait data using two smartphones, one attached to the right thigh and another one on the left side of the waist. This data is collected to be utilized by a deep learning-based method that requires enough time points. The metadata including age, gender, smoking, daily exercise time, height, and weight of an individual is recorded. This data set is publicly available.
Introduction

Biometric recognition refers to the identification of individuals through biometric measures through his/her physiological (e.g., face, hand) or behavioral characteristics (e.g., gait, writing style)[1]. Gait, as a behavioral biometric modality is a useful and reliable approach that identifies individuals based on their walking patterns, and recently has a gain interest in multiple research domains such as applications in forensic science, surveillance, and security[2–6]. There are several reasons why gait recognition is preferred over the other biometric identification and authentication techniques. First, unlike the techniques using fingerprint or retinae scan, gait can be measured continuously and remotely over time, second It is a non-invasive measure as acquiring gait does not impact individuals’ comfort zone. Moreover, since it is a behavioral biometric authentication technique, it is harder to steal and cannot be forgotten, another reason is that compared to other behavioral biometrics such as fingerprint, gait is a more secure modality because the gait of an individual is difficult to mimic[7]. Lastly, a person’s gait can be recognized even under adverse conditions[8].

Many databases have been developed and used for authentication and identification purposes [9–15]. However, they are either not publicly available [9,10,13,14,16], or if they are publicly available they have their own limitations [11,12,17]. Designing automated human identification or authentication systems requires a proper dataset. Among the publicly available datasets, the largest one was acquired by researchers at Osaka University (OU)[17]. Although they constructed several datasets with three inertial sensors and a smartphone around subjects’ waists and included a large number of subjects (744), they only recorded two very short data sequences for each subject, and their data collection was done under controlled conditions. A short sequence of data in this dataset limits the application of deep neural networks. Other publicly available datasets are including data from a much smaller number of participants [9,10,15].

To overcome some of these limitations, in this study gait data was collected from 93 individuals using iPhone 6s, attached to the left waist and right thigh of the participants (Figure 1). For each subject, two acquisition sessions were conducted covering about 320 meters (200 miles). Participants were asked to walk at their comfortable speed. The sampling frequency for collecting the raw inertial signals was 100. This database offers the following advantages over existing databases:

- A large number of subjects can significantly improve the performance and reliability of the gait recognition algorithms.
- Large enough time points to be trained by machine learning-based algorithms.
- The male-to-female ratio is close to 1. A biased gait recognition system is prevented by this property.
- Our 6D gait signal includes 3D acceleration and 3D angular velocity capture data high frame rate, which is not only useful for gait recognition but also for understanding the walk motion.
- Individuals’ metadata, including exercise level and smoking, could be used further for gait analysis of different populations with regard to these aspects. This dataset would be particularly useful for variability analysis because taking more than 30 steps is recommended to maintain gait variability reliability.
- Variation of sensor locations (left waist and right thigh) could be useful in comparing the performance of the gait recognition systems and their dependence or independence on the body location where the sensor is attached.
- This dataset can be used in integration with other future datasets for Identifying walking from other activities.
Our database has the limitation that different conditions (e.g., clothing, ground slope conditions) were not considered during data collection. Additionally, we did not collect data on different walking speeds.

Figure 1. Two smartphones are mounted on the right and left thighs, respectively.

Experimental design, materials and methods

Data Collection

This study was conducted by recruiting 93 individuals who walked at a comfortable pace during two different sessions. First, the participant gave verbal consent after explaining the details of the experiment and answering her/his questions. Then, we collected participants' personal information, as well as took their body measurements, including their weight, age, height, and information about their exercise habits, smoking habits, and gender. Figure 3, histogram of age, weights, sex, and, exercise time per week of subjects to have a better understanding of their distributions. The data is recorded on two smartphones (iPhone 6S) in each session, one on the waist and the other on the thigh, as shown in Figure 1. During each session, each subject walked 320 meters between two endpoints, A and B, forward and backward (a total of 640 meters). The experiment was conducted at the same location with the same sea level of 0 for all subjects. For each individual, one smartphone was first installed near the left waist and then the other smartphone was installed on the right thigh. To remove the setup noises, the subject had to wait for 5 seconds after installing the smart phones and after 5 seconds, he/she started to walk from endpoint A to endpoint B. Upon reaching point B, the subject turned around and waited for 5 seconds before walking back toward
point A. After the subject arrived at point A, he/she waited for 5 seconds and then the smartphones are detached, and data collection stopped. Five-second interruptions are used to identify directions. The same experiment was repeated for the second session. To capture the data, we used the SensorLog application (v1.9.7), which is developed and tested for the IOS framework. Figure 4 shows a scatter plot of accelerometer values consisting of X, Y and Z coordinates before and after removing noises such as standing timepoints.

Data description
We provide 4 different log files to include information associated with every subject who attended the experiment, except 19 subjects who did not attend the second session (each session contains two log files).

Every file name has one of the following patterns:

- sub0-lw-s1.csv: subject number 0, left waist, session 1
- sub0-rp-s1.csv: subject number 0, right thigh, session 1
- sub0-lw-s2.csv: subject number 0, left waist, session 2
- sub0-rp-s2.csv: subject number 0, right thigh, session 2

Every log file contains 58 features that are internally captured and calculated using SensorLog app. Figure 2 represents all the 58 features based on each category. Additionally, an Excel file containing the metadata is provided for each subject.

![Figure 2. 58 features that are logged and calculated by SensorLog app. These features divided into 7 categories that are represented by each color.](image)

**Use Cases**

Many studies have been conducted on gait datasets based on varieties of deep learning and machine learning algorithms. Stefano et al., used LSTM recurrent neural network to deal with time-dependent information within brain signals during locomotion[18]. Davarzani et al., used ANN, and LSTM to model human gait recognition[19]. Xiuhui Wang and Wei Qi Yan used Conv-LSTM for Human Gait Recognition[20].

In this study, using the collected data set, we present general recurrent neural networks (RNNs) for gait biometric recognition. The accelerometer signals are typically sequential data that are appropriate to be analyzed by an RNN. In the past, gait biometrics were handled using handcrafted features, which resulted in complex algorithms computation and heavy reliance on experimental design. The proposed model can automatically learn the dynamic features and temporal dependencies from a short data window (128 points) extracted from a sequence of raw accelerometer signals. We evaluated the model on the data set and the results show that the proposed model significantly outperforms the previous studies in this field, which in turn, indicates the quality of the data set.

**Data Preprocessing**
Data has been processed in five steps as follows.

1. **Cleaning Data**: Removed 24 subjects since their left waist data and right leg pocket data cannot be aligned according to the timestamps.
2. **Determining Z axes**: Computed the absolute mean value of each axis, and the axes with the maximum values are Z axes. Remove gravity offset (1.0) from Z axes.
3. **Data combination**: Aligned left waist data with right leg pocket data based on timestamps to form a 6-channel space (Xlw, Ylw, Zlw, Xrp, Yrp and Zrp).
4. **Splitting data**: Used a sliding window of fixed length to segment the data without overlapping. The window length is 128, corresponding to the step size of our model. The total number of sequences obtained after this configuration is 32,556. Each sequence has a size of 128 × 6, which is an input of our model.
5. **Standardization**: Applied a non-linear transformation (QuantileTransformer) such that the probability density function of each feature will be mapped to a normal distribution. The transformation smooths out unusual distribution and is robust to outliers.

**Model implementation**

Our model referred to as GaitNet, is a 3-layer Gated Recurrent Unit (GRU) neural network with 64 units on each layer (Figure 5), which takes as inputs a fixed-sized sequence of raw gait points extracted by a sliding window approach. Each gait point is a 6-dimensional feature vector, consisting of X, Y and Z coordinates collected from smartphones on both spots, denoted as Xlw, Ylw, Zlw, Xrp, Yrp and Zrp. Using the input gait data, the model can automatically learn the dynamic features and temporal dependencies and output a probability distribution over all classes. With increasing numbers of points seen by the model, the cell state of the model becomes increasingly informed. Therefore, we are only interested in the prediction output at the last time step, when the full sequence has been observed.

![Figure 5: The Architecture of GaitNet](image)

**Training**
The data set was randomly divided into 80% for training, 10% for validation, and 10% for testing. GaitNet was trained on 27,036 data windows of length 128 time steps for a total of 31,535 iterations using mini-batch gradient descent with a learning rate of 0.001. The batch size was set to 30. A Softmax classifier was used to calculate the probability distribution over 69 classes and the model was trained by minimizing the cross-entropy loss between predicted probabilities and one-hot encoded target. Adam (Adaptive Moment Estimation) optimizer was used to update the weights with gradient clipping to control the exploding gradients problem. A dropout regularization with a rate of 0.5 was applied to each RNN cell to avoid overfitting. To monitor convergence and overfitting problems, the model was validated every 200 iterations on the validation set. In addition, the validating result was also employed to pick the best model after training. Our model took approximately 5 hours to train on NVIDIA GTX 1080 Ti running Tensorflow 1.3.

**Results**

A biometric recognition system can run in two different modes: identification or verification. We use Rank-1 identification rate (Rank-1 IR) and Equal Error Rate (EER) for the evaluation of biometric identification and verification performance, respectively. Our GaitNet model works as a multiclass classifier that can yield a class probability distribution for an input gait movement pattern of a person who is going to be identified. By comparing the prediction probability to a decision threshold, the model decides whether to accept or reject a person. Rank-1 IR is a measure of biometric identification performance that shows the percentage of correct identifications returned at the first place of a ranked list. The achieved Rank-1 IR for our model is 99.1%. In the verification scenario, the decision threshold must be adjusted according to the desired characteristics for the application considered. The equal error rate (EER) can be used to give a threshold independent performance measure of a biometric system. GaitNet achieves 0.31% EER. In Fig. 3, we also present the ROC curves to provide a more global overview of the biometric recognition performance. The ROC curve is plotted in logarithmic scales (i.e., x-axis in logarithmic scale) since low false acceptance values are of more interest, and the logarithmic scale better distinguishes these values.

![Figure 6. The constructed ROC curve demonstrating the overall verification performance of GaitNet.](image)

**Supporting Information**
The trimmed accelerometer dataset and meta data can be downloaded [here](https://doi.org/10.6084/m9.figshare.20346852.v1)

**Ethics statements**
Each participant was provided with information about the study and provide verbal consent. The study was approved by Computer Science Department at University of Massachusetts Boston prior to conducting the study.

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**Declaration of interests**
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
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