The MMUISD Gait Database and Performance Evaluation Compared to Public Inertial Sensor Gait Databases

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Abstract. Gait recognition is an emerging biometric method that allows an automatic verification of a person by the way he or she walks. This paper presents a new dataset for gait recognition using mobile sensors called MMUISD Gait Database that resembles the real world as closely as possible. The existing public gait databases are acquired in controlled settings. In this study, an Android application is developed to record the human gait signals through inertial measurement unit sensor such as accelerometer and gyroscope with 50 Hz fixed sampling rate. A preliminary evaluation with 80 samples of participant's data is carried out to assess the gait recognition performance using the new dataset. Time and frequency domain are used to extract gait features from the raw sensors data. The accuracy is assessed using eight classifiers with 10-fold cross validation. The results show that phone positions and orientation affect the gait recognition performance. The MMUISD dataset that introduces such variability provides a good opportunity for researchers to further investigate these challenges.

Keywords: Inertial Sensor, Gait Recognition, Gait Dataset.

1 Introduction

In recent years, studies have been conducted on human gait for physical activity recognition, especially in the areas of healthcare systems, assisted living, biometrics and security [1]. There are two types of gait analysis: video-based and sensor-based. Due to the rapid development of smartphones including embedded sensors in the smartphone, sensor-based methods have received increased attention because it is unobtrusive and user friendly. Recent studies for human gait incorporate the fusion of Inertial Measurement Unit (IMU) sensors (accelerometer and gyroscope) to analyze the gait characteristics [1][2]. It is shown that the fusion of both sensors can improve the recognition performance as they complement each other. Moreover, it has been reported in [3] that the built-in accelerometer and gyroscope are very stable in performance based on evaluation with regards to the accuracy, precision, maximum sampling frequency, sampling period jitter and energy consumption.

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However, most of the previous studies analyzed the motion sensors in controlled scenarios. For instance, the experiments were conducted with fixed sensor placements and predetermined fixed orientations [1][2][4][5][6], and with particular type of outfit and shoes [7]. In fact, it is not possible to control the orientation and the sensor placement in reality. Besides, it is important to note that the data were collected using the same phone [1][2][3][4][8][9]. This makes it difficult to confirm the superiority of an algorithm on a new dataset as different smartphone manufacturers use different types of sensors in their devices. The authors in [5] had conducted a test to assess the heterogeneities of mobile sensing for activity recognition with 13 different device models from four manufacturers. Although they used various device models, the experiment was performed under fixed laboratory settings.

This paper presents a new dataset called MMUISD Gait Database. The uniqueness of this dataset includes: (1) different types of Android phones were involved, (2) different phone placements, and (3) both the accelerometer and gyroscope signals were recorded. This paper is structured as follows. Section 2 describes the related work while the data collection experiments are elaborated in Section 3. Section 4 describes data preprocessing and the performance evaluation results. Finally, in Section 5 we summarize our conclusions and future research.

2 Related Work

2.1 Existing Public Gait Databases

The authors in [1] performed data collection by fixing the sensor placement. There were only a few participants in the study, and there were age range and gender biases. A study from [2] presented the largest database for human gait inertial sensor with a large number of participants, and wide range in gender and age. They used accelerometer data from smartphone for 408 subjects out of 744 subjects while the rest is collected with the IMUZ sensors (accelerometer and gyroscope). However, the sensor placement was fixed at the waist of the participants. Furthermore, [5] and [10] only explored the motion sensor from a single body position. The number of participants was limited, and the sensor was fixed at the waist. The sensor orientation was predetermined.

A comparison of the existing public inertial sensor-based gait datasets is presented in Table 1. Overall, the gait databases were collected under controlled environment due to several constraints from the smartphone to produce a reliable and consistent data collection. Hence, there is a need to collect real life data to ensure that the wearable sensor data can be used for real practical applications.

2.2 Gait Recognition Methods

Some researchers performed feature extraction on the time and frequency domains and classification was conducted with machine learning classifiers [1][5][10][11][12][13]. Apart from that, template matching approach with various distance metrics was also used to extract gait templates which represent the most defining characteristic of the subjects [5].

Table 1. Existing Public Gait Database

Dataset	Partici-pants (Age/ Gender variation)	Smart-phone Type	Sensor Description	Activity
Pervasive [1]	10 (males, age 25 and 30)	Samsung S2 (i9100)	Portrait left and right pocket, right upper arm, right wrist, on the belt position with belt clip (Accelerometer and Gyroscope 50 Hz)	Walking, sitting, standing, jogging, biking, walking up/down stairs (each of activities 3-4 minutes)
UCI HAR [5]	30 (age 19-48)	Samsung S2	Waist (Accelerome-ter and Gyroscope - 50 Hz)	Walking, walk-ing-upstairs, walking-down-stairs, Sitting, standing, laying
UCI HAPT [10]	30 (age 19-48)	Samsung S2	Waist (Accelerome-ter and Gyroscope - 50 Hz)	standing, sitting, lying, walking, walking down-stairs and walk-ing upstairs with Postural Transi-tion
OU ISIR [2]	408 (age 2-78, 219 males and 189 fe-males)	Motorola ME860	Center back waist (Accelerometer 100 Hz)	Two different level-walk se-quences (entering and exiting) on flat ground
Our Dataset (MMUISD)	299 (age 18 – 28, 246 males and 53 fe-males)	Various Android phone	Carry by hand (left and right), place in trouser pocket (left and right), back-pack and handbag (Accelerometer and Gyroscope – 50 Hz)	Walking on flat ground corridor with 3 different speed (slow, nor-mal, fast)

In [1], the authors evaluated four feature sets using nine classifiers with WEKA 3.7.10. It was found that when the individual performance of the sensor was not very high, the fusion of sensors improved the overall recognition performance. Next, in [5], 561 features in time-frequency domain and ECDF were evaluated with four classifiers and cross validation. The result of the study showed that human activity recognition performance is significantly impaired by sensor handling heterogeneities and the type of recognition technique also played an important role. Meanwhile, a study from [10] used PrSVM classifier with TFilt to evaluate 561 features data for the Activity Learning

(AL) and Activity Transition Learning (ATL). The performance of their proposed architecture was measured with the system error at different locations of the architecture pipeline and they obtained 3.64% and 3.22% for the system error for AL and ATL, respectively. On the other hand, a study from [2] used gait periodic detection from previous research study and calculate the similarity score with two normalized distance measures and two unnormalized distance measures. The magnitude of a 3D accelerometer signal was used for the evaluation since change of sensor orientation does not affect the magnitude of signal. The performance result was evaluated using receiver operating characteristic (ROC) curve and it can be concluded that the authentication performance was slightly influence by the position of the accelerometer since the acceleration depends on the location of the sensor.

3 Data Collection

An Android application was developed to capture the data with 50 Hz fixed sampling rate. Studies have shown that this sampling rate is sufficient for activity recognition [1]. The definition of a realistic world scenario is quite subjective so several studies have been conducted [14][15] to know how smartphone users often carry or place their phones. We also conducted an online survey to decide the sensor placement [16] based on the participants' top voted choices.

The dataset was taken in Indonesia and Malaysia. The reason for this is to have a larger dataset comprising of individuals from different races, geographies and environments which increases the diversity of habitual gait. A total of 299 undergraduate IT and Engineering students (246 males and 53 females) with ages ranging from 18 – 28 years participated in the database collection process. Informed consents were obtained for data collection for the ethical conduct as part of the regulation of Multimedia University.

The participants were formed in groups to make the data collection process more organized. Each of the participant was asked to install the application on their phones. If the participant's phone was not equipped with both sensors (some of the smartphones only have accelerometer but not gyroscope), the other group member's phone was used.

The data collection process was carried out in a corridor inside the university building. The phones were fixed at six positions, i.e. left and right pocket, in a hand carry bag, in a backpack, and in the left and right hand (see Fig. 1). Each subject performed three different walking speeds: slow walk, normal walk and fast walk. The participants were told to walk naturally for the three walking speeds without any constraints. It took around 5-8 minutes for each subject to perform all the walks at 3 different walking speeds. In the transition to change the walking speed, they were asked to stop for 3 seconds at the turning points before walking back to the initial point.

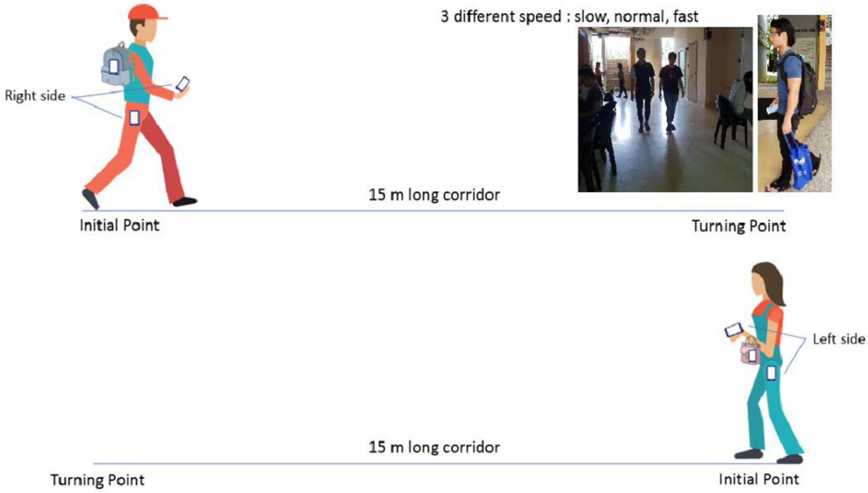

Fig. 1. The data collection protocol with an overview of the phone positions on a participant.

4 Data Preprocessing and Performance Evaluation Analysis

Eighty participant's data (40 data from Indonesia and Malaysia, respectively) were selected randomly from the MMUISD gait database for preliminary evaluation due to time constraints in preparing the data for full performance evaluation. For a fair comparison, the results are compared to the existing public gait databases using the same protocol including data preprocessing methods and classifiers (except for [5] and [10] as the datasets already contained 561 extracted features). The comparison of recognition accuracy shows the difficult level of our dataset as our dataset contains noise and orientation problems (i.e. screen rotation during walk when carried with hand or put in the handbag or backpack). Furthermore, we did not perform any algorithm to overcome the orientation problem.

4.1 Data Preprocessing

Some noise (abnormal spikes) occur when the application is first started. After the completion of the walking activity, some irrelevant signals also occurred due to non-gait related activity like putting the smartphones away when the application is stopped. Additionally, when the participants need to repeat the same walk and perform a turn, this also causes some noise during the transition. Therefore, some noise removal processes are required to remove the noise. First, the raw signal is segmented into three parts: slow, normal, and fast. The signal is manually segmented by observing the abnormal spikes which denotes the transition between changes in walking speed. After segmentation, the signals from the three axes of accelerometer and three axes of gyroscope are normalized with z-score as shown in Equation 1.

$$Z_i = \frac{X_i - \bar{x}}{\sigma} \; i \in x, y, z. \quad (1)$$

$$m = \sqrt{x^2 + y^2 + z^2} \quad (2)$$

The resultant vector from the magnitudes of individual acceleration and gyroscope is calculated using Equation 2 from the normalized data in order to minimize the effect caused by orientation changes [1][17]. Thus, each sensor will have four dimensions, i.e. $(x, y, z, magnitude)$. A window containing 100 data points with 50% overlap is selected to extract different features which represent the characteristics of gait signal in time and frequency domain [1][18]. The extracted features include mean, standard deviation, variance, minimum value, maximum value, auto correlation mean, auto correlation standard deviation, auto covariance mean, auto covariance standard deviation, skewness, kurtosis, median absolute deviation, root mean square, interquartile, entropy, energy and sum of first five FFT coefficients. Thus, a total of 136 features were used to represent the gait signatures.

4.2 Performance Evaluation Analysis

The recognition performance is evaluated using eight baseline classifiers. The true positive rate given by Equation 3 is used as the evaluation metric,

$$TPR = \frac{(TP+TN)}{N} \quad (3)$$

The features data are divided into 80% training and 20% testing. Then with 10-fold CV each feature vector was randomly assigned to one of the 10 subsets. The study will classify user ID using machine learning algorithms. The classifiers used to measure the accuracy include Logistic Regression (LR), Linear Discriminant Analysis (LDA), Multi-layer Perceptron (MLP), Decision Tree (DT), Random Forest (RF), Gaussian Naive Bayesian (NB), Gradient Boosting (GB) and Support Vector Machine (SVM). The short notations for the classifiers are used for brevity henceforth.

The accuracies on the different datasets are presented in Table 2. The results reveal several important observations. First, OU ISIR dataset yields the lowest accuracy among the other dataset, this shows that the wide range of age and gender, and a larger dataset influenced the gait recognition performance. Second, Pervasive dataset yields the highest accuracy for Random Forest and Linear Discriminant Analysis classifier among the others dataset. This is possible because the number of samples is small (containing only 10 participants). Moreover, the sensor was placed at the participant's bodies thus the orientation is fixed and contains less noise. Note that this scenario is not always possible in a practical situation. Third, the classification accuracy might be improved with the total number of features (refer to UCI HAR and UCI HAPT with 561 features respectively). However, higher number of features only make the computation time longer.

In Table 2, "MMUISD Normal" trial refers to the performance evaluation of our dataset for normal walking speed using all sensor positions, which are phone in pocket, carry by hand, backpack, handbag or goody bag. Our dataset gives a relatively lower accuracy as compared to the existing public gait datasets except OU ISIR. This shows our new dataset impose challenges for gait recognition. The reason why the results for OU ISIR is lower than MMUISD is because the OU ISIR dataset contains a much larger subjects as compared to our dataset. Besides, the OU ISIR dataset only contains accelerometer signal while MMUISD contains both accelerometer and gyroscope signals. The fusion of both sensors might also lead to better performance of the MMUISD dataset.

Table 2. Classification accuracy for existing public gait database.

Trial	LR	MLP	SVM	DT	**RF**	GB	LDA	NB
OU ISIR	16.67	1.96	0.25	4.41	**26.72**	4.17	26.23	9.07
UCI HAR	77.09	91.21	80.56	81.1	**92.32**	84.84	72.47	21.96
UCI HAPT	74.13	75.74	79.60	79.66	**90.21**	82.11	69.75	21.68
Pervasive	98.75	99.38	95.62	98.12	**99.38**	96.88	**99.38**	98.75
MMUISD normal	42.36	28.82	1.41	38.84	**53.87**	53.69	51.76	25.13

Next, we assess the performance of the MMUISD dataset by segregating the phone signals by walking speed and sensor position. Short notations as seen in Table 3 are used to represent the results in Tables 4 to 6 for each activity in the dataset collection process. For example, "Slow_L1" refers to the data for slow walking speed with the sensor in the left of the front pocket.

Table 3. Short notation for walking speed and sensor position.

Notation	**Description**
L	Left
R	Right
1	Pants front pocket
2	Backpack
3	Hand bag or goody bag
4	Carry by hand

Tables 4 to 6 present the results for slow, normal and fast walking speed for all positions. We analyze the sensor positions for slow, normal, and fast walking speed to see which sensor position gives the best result and which classifier has the best performance. We observe that the performance trends between the left and right pocket position, and also between the left and right carry by hand position are quite similar. This result reaffirms findings in the previous studies [1]. In Tables 4 to 6, the LDA classifier shows the highest accuracy for the all sensor positions, meanwhile the lowest accuracy is reported for SVM. To the best of our knowledge, the success of the classification does not depend on the classification method, but rather on the nature of the data. For some data, one technique might perform better, for another sample it will be another technique. This finding is also consistent with the results reported by [13].

Table 4. MMUISD classification accuracy for the slow walking speed.

Trial	LR	MLP	SVM	DT	RF	GB	**LDA**	NB
Slow_2	58.27	11.81	0.24	38.58	49.61	33.86	**85.83**	57.48
Slow _3	40.16	11.02	0.09	23.62	33.07	19.69	**62.28**	39.37
Slow_L1	59.84	12.69	0.37	36.22	51.97	30.71	**86.61**	59.84
Slow_R1	57.48	9.45	0.28	44.09	48.82	29.13	**87.49**	51.97
Slow_L4	46.46	11.02	0.19	23.62	31.59	16.54	**77.17**	44.88
Slow_R4	53.54	14.17	0.13	33.86	43.31	32.28	**80.31**	55.12

Table 5. MMUISD classification accuracy for the normal walking speed.

Trial	LR	MLP	SVM	DT	RF	GB	**LDA**	NB
Normal_2	69.29	27.56	0.16	51.97	71.65	47.24	**83.79**	62.29
Normal_3	25.27	11.81	0.89	15.75	33.07	17.32	**66.93**	37.86
Normal_L1	61.42	25.98	0.76	51.18	68.59	48.03	**80.55**	59.06
Normal_R1	58.73	13.49	0.57	45.24	58.73	36.51	**80.48**	64.29
Normal_L4	52.76	19.69	0.68	33.86	42.52	33.86	**80.31**	46.46
Normal_R4	48.82	18.95	0.54	32.28	44.09	29.92	**81.18**	54.33

Table 6. MMUISD classification accuracy for the fast walking speed

Trial	LR	MLP	SVM	DT	RF	GB	**LDA**	NB
Fast 2	67.13	35.66	1.39	48.25	67.83	51.75	**86.01**	67.83
Fast_3	39.64	15.32	0.12	18.92	30.63	18.92	**66.67**	34.23
Fast_L1	65.77	31.53	0.91	40.54	63.96	44.14	**83.69**	52.25
Fast_R1	51.58	26.32	0.89	45.26	57.89	32.63	**82.11**	48.42
Fast_L4	50	32.54	17.46	32.54	40.48	33.33	**73.02**	39.68
Fast_R4	43.65	26.98	16.67	39.68	40.48	35.71	**75.4**	49.21

The results for handbag or goody bag yield the poorest performance as compared to the other positions. The performance result for backpack is better than goody bag or hand bag, and is almost similar to the results of the other positions. During the data collection process, the participants used their own backpack which was usually filled with belongings. This could be the reason why the performance for backpack is better than handbag or goody bag position. The movement of the sensor in the backpack is limited by other objects inside the backpack. On the other hand, the handbags and goody bags provided to the participants are empty which cause large oscillation when the participants walk. This results in undesirable patterns like spikes in the gait signal due to irrelevant movements such as swinging of the bags while walking.

4.3 Discussion

There are several interesting observations from the experimental results:

- The highest accuracy was achieved for the backpack, left and right pocket sensor positions. This suggests that putting the phone in such positions (like inside the pants pocket and backpack) produces data that are easier for gait recognition. In

comparison, for the phones being carried by both the left and right hands yield poorer performance, but it performs better as compared to the sensor placed inside the hand bag or goody bag.
- Phone orientation plays an important role for the recognition performance this finding reaffirms with the previous studies in [19]. For example, result for phones placed inside the pocket is better than that carried by hands. Phones in hands are subject to higher variation in their orientations due to hand swaying movement.
- Different type of Android phone does not affect the classification performance as we observed the results from gait recognition performance in Tables 4 to 6 show almost similar pattern even though the data are from various phones. The findings also show that regardless of the walking speed, the highest accuracy achieved is still dependent on phone positions.
- The fusion of accelerometer and gyroscope helps to improve the gait recognition performance, this finding goes in line with previous study in [20]. The results for public gait database (from smartphones) containing only signal from a single sensor [2] produces inferior results compared to dataset comprising both accelerometer and gyroscope signals [1][5][10].

5 Conclusion and Future Work

The construction of a gait database that resembles the real world as closely as possible is described in this paper. Preliminary evaluation is conducted to compare the gait recognition performance between varying phone placements and walking speeds. The results are also compared with the benchmark gait databases. Preliminary analysis shows that the proposed dataset can contribute to the gait recognition research community to develop techniques to overcome the sensor position and orientation problems. Compared to previous works, we provide researchers with a challenging dataset to meet the demand of practical application. More samples from more volunteers will be incorporated as this research is still on-going. Further study will be performed to improve the gait recognition performance using our dataset with respect to real practical scenario.

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