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Age Estimation and Gender Classification Based on Human Gait Analysis

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***Abstract*— Human gait is an important biometric trait which is used in a variety of applications. The development of low-cost inertial sensors has facilitated the capturing of human gait, widening its use in commercial applications. This study proposes a method for gender classification and age estimation using the largest available inertial sensors human gait dataset. The proposed method has three stages. Identification of human gait cycles from inertial sensors signals is performed at the first stage. At the second stage, statistical features are extracted from identified gait cycles. The features extracted at the second stage are used in various machine learning algorithms for gender classification and age estimation at the third stage. A series of experiments are performed, and results show the effectiveness and promising potential of the proposed method for age estimation and gender classification.**

Keywords—age estimation; gender classification; human gait; inertial sensors

I. Introduction

The use of inertial sensors (accelerometers, gyroscopes) for gait analysis has become popular in recent years due to the recent development in microelectromechanical systems (MEMS). The inertial sensors offer an easy and low-cost measurement as these can be embedded in devices which we use in daily life e.g. mobile phones, smart watches etc. Gait is an important biometric feature which helps in identification of humans and their actions and it can be used in a variety of applications including authentication, security, biomechanics, sports and medical field [1].

A detailed survey of existing parameters, techniques and databases used by researchers in the field of gait analysis is presented in [1]. In this paper applications of gait analysis in clinical diagnosis, geriatric care, sports, biometric and rehabilitation are presented along with future perspectives. Sparger and Juric [2] presented a detailed review of inertial sensors-based gait recognition. They predicted that this research field will receive a lot of attention in coming years as demonstrated by the number of research works carried out in this field in the last decade. They pointed out the potential of inertial sensors-based gait recognition in terms of applicability and usability with advancement in technology.

Zhong and Deng used i-vector paradigm for extracting gait identities for performing user authentication [3]. They used the Osaka University dataset [4] and McGill University dataset [5] for demonstrating the superiority of their proposed method. Gafurov, Snekkenes and Bours attached an accelerometer with ankle for measuring 3d acceleration signals for user authentication [6]. They collected the data of thirty subjects and achieved an equal error rate (EER) of 5.6%. They also showed through analysis that authentication was better with light weight shoes compared to heavy weight shoes. Ren et al. used a smart phone at 50Hz sampling rate for collecting accelerometer data of 26 subjects under different conditions [7]. They presented a detailed analysis on step cycle identification from gait data. A user-centric scheme based on similarity score comparison and a server-centric scheme based on Support Vector Machine (SVM) was presented for identification under spoofing attacks. Sprager and Juric [8] used higher order statistics for feature extraction from accelerometer data for gait authentication. The experiments were performed on OU-ISIR and McGill University data and EER of 6-12% was reported. Zou et al. used inertial as well as RGBD sensors for gait analysis and user authentication [9] asserting that a single sensor leads to fragile identification system. The data was collected from 50 subjects and the extracted features from both sensors were fed to a supervised classifier for identification. Higher accuracy and robustness were reported using the proposed system compared to other state of the art systems.

Youn et al. [10] used various machine learning algorithms for classifying subjects into two age groups using OU-ISIR dataset. A combination of 24 statistical features was used in machine learning algorithms and an accuracy of 81% was reported. Wei et al. used RBF neural networks for user authentication using OU-ISIR and reported 83.8% accuracy [11]. A lot of methods have been proposed in literature for estimation of age through human gait but most of these methods are image processing based where silhouette of humans is used for age estimation [12].

There is very limited literature available on age estimation using motion sensors data and that literature uses a small dataset and mostly determines the age group of a person without determining the exact age of a person [13–14], [19]-[20]. Kelishomi, Cai and Shayesteh [13] used smart phone-based accelerometer and gyroscope data for estimation of age group, footwear and floor surface type. The number of subjects was 510 and 262 features were extracted from the measured data. A random forest classifier was used and an accuracy of 85% for age group classification from age 20 to 60 with an increment of 5 was reported. Davarci et al. used mobile phone for collection of accelerometer data from 200 subjects (100 children (3 to 11), 100 adult (12 to 50)) and sixteen features were collected from the data [14]. Logistic regression (LR), KNN and random forest (RF) were used for classification whereas Principal Component Analysis (PCA) was used for dimension reduction. An accuracy of 89% was reported for classification between child and adult.

Generally, two steps are performed for age estimation or gender classification where features are extracted at the first step and regression/classification in performed at the second step. Although these steps work fairly well for image-based gait analysis, 3D to 2D projections, occlusion, scaling etc., pose serious limitations in precise motion estimation using images resulting in inaccurate estimation of gait characteristics. Sensor based gait analysis does not suffer from aforementioned limitations and provides a more accurate and inexpensive method for precise gender classification and age estimation [19]-[20] and the same method has been used in this study.

This research has used the largest inertial sensor data base [4] for age estimation and gender classification using various machine learning methods. To the best of our knowledge, this is the first attempt to predict age using gait analysis on such a large and diverse dataset. The paper is organized as follows: Introduction is given Section I. Section II describes the dataset used in this research. Methodology is presented in Section III while Section IV is about experiments and results. Conclusions are drawn in section V.

II. DATASET

There are many databases which have been used for gait analysis using inertial sensors but most of these databases are very small with total number of subjects around or less than 100 [1]. Moreover, most of these databases are either gender biased with number of males much larger than females [4] or these are age biased with adults being the dominant subjects.

The database used in this study is collected by the Institute of Scientific and Industrial Research (ISIR), Osaka University (OU) in Tokyo Japan in 2011 (known as OU-ISIR). There was a total of 744 subject (388 males and 356 females) with ages from 2 to 78 years. A distribution of the subjects in terms of age and gender is shown graphically in Figure I. The gender wise distribution is quite similar for male and female while the distribution in terms of age is highly varying for both genders. There is heavy concentration of subjects from age 5-15, 35-45 and 20-25. Distribution at all other ages is quite sparse.

Three IMUZ (Inertial Measurement Units) sensors each having a triangular accelerometer and a triangular gyroscope were used for capturing the inertial signals [4]. Two sensors were attached to side of waist while one was attached at center back of waist. All the sensors worked at 100 Hz. A smart phone with accelerometer and gyroscope sensors can also be used in place of IMUZ. Signals were recorded while subjects were asked to walk on a designated path once entering the path (Sequence (seq) 0) and once coming back on the same path (Sequence (seq) 1). An example of accelerometer and gyroscope signals for first subject of the dataset for seq 0 is given in Figure 2. A clear repeating pattern can be seen for all the signals. The repeating pattern is due to the repeating gait cycles as the subject walks.

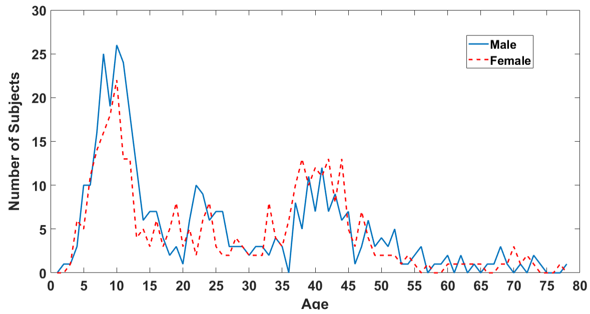

Fig. 1. Age distribution of males and females in OU-ISIR dataset

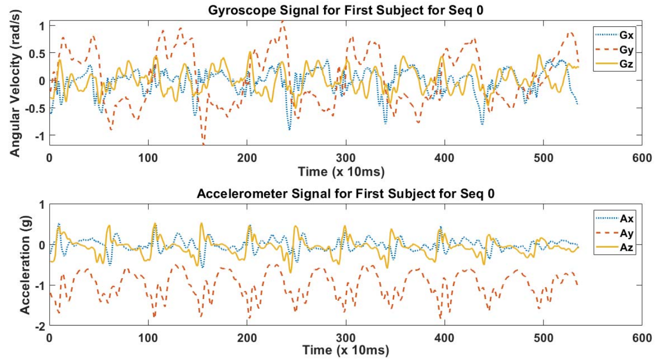

Fig. 2. Gyroscope and Accelerometer signals for a subject along x, y and z directions for one (center) IMUZ

III. METHODOLOGY

There are three basic steps for age estimation and gender classification based on human gait; 1) Gait cycles identification 2) Extracting relevant information (features) from gait cycles 3) Using features in algorithms for age estimation and gender classification. These three steps are described in detail in the next three subsections.

A. Gait Cycle Identification

Human walk is a periodic activity during which at one point one foot is in air while the other foot is on the ground and then these feet change their activity. A single pattern of these activities by one foot is known as one gait cycle. In any gait-based application, it is important to correctly identify gait cycles as all the processing performed later depends on it. There are two popular methods to extract information related to gait cycle; 1) Using fixed time windows and extracting features from each window 2) identifying actual gait cycles and extracting features from each gait cycle. The first method has low computational complexity and is quite popular in activity recognition algorithms [15]. The choice of the size of the window and the overlapping interval between the windows are two factors which depend on the data at hand and seriously affect the performance of this method. The second method although more complex but may give more accurate results if the gait cycle is identified correctly. Accurate detection of start and end of a gait cycle is a challenge for this method especially for a large dataset with diverse age range. The speed of a movement of a subject poses a challenge in accurate detection of a gait cycle and this speed varies a lot from young to old.

In this research a method presented by Ren et al. [7] has been used for gait cycle identification. In addition to the three accelerometer (*Ax, Ay, Az*) and three gyroscope signals (*Gx, Gy, Gz*), two more signals have been added to the original signal dataset. The two added signals are the magnitude of three accelerometer and gyroscope signals which could be computed using this equation $\sqrt{(A^2_x + A^2_y + A^2_z)}$. In total eight signals were used for the identification of gait cycle in the beginning and the best out of these eight for gait identification was chosen. Experiemnts were performed for gait identification using all eight signals independtly and it was found through experiments that the accelerometer signal in z direction (*Az*) was the most useful signal for gait identification so only this signal was used for all the experiments in this study for gait identification.

During walking, there comes a point when both feet are on ground and vertical acceleration (*Az*) at that time is zero which can be observed as a local minimum for *Az*. The first two local minimums represent half gait cycle while first and third local minimums represent full gait cycle as shown in Figure 3. The detection of actual local minimums (represeting feet at ground) is not an easy task due to irregular body movements and variation in walking speed. The general strategy used by researchers is to identify first gait cycle and then use it to identify following gait cycles [7]. In this case, identification of all following gait cycles is dependent on accurate identification of first gait cycle. If first gait cycle is not identified correctly, the error propagtes to the following gait cycles. This study uses the maximum, minimum and average number of step cycle samples to identify the first gait cycle [7] and then uses the correlation between the first and subsequent gait cycles to identify all remaining cycles. All the cycles are interpolated to same number of samples for facilitating processing of gait cycles. The method could be described in three steps.

1) First Gait Cycle Identification

The identification of first gait cycle depends on accurate marking of first (*T1*) and third local minimum (*T2*) which represent the start and the end of the first gait cycle. To identify *T1*, maximum (*M'*) and average gait cycle (*M*) samples have been collected based on a study presented in [7]. An average human irrespective of the walking speed, takes 45-65 gait cycles/minute [7]. With a sampling frequency of 100 Hz, the maximum number of samples in a gait cycle are 133 (*M'*), the minimum number of samples is 92 while the average number of samples (*M*) is 112. The first minimum (*T1*) can be found by starting from the first sample and looking for minimum in first *M'* samples as shown in Figure 3. The third minimum (*T2*) could be find *M* samples away from *T1*. Since the subject's walking speed might be changing, the condition for *T2* is relaxed. *T2* could be found $M \pm d$ samples away from *T1* where *d* is the average of the difference between the maximum and minimum samples in a gait cycle (i.e. d = (133-92)/2). The whole process of finding *T1* and *T2* is shown in Figure 3.

2) Gait Cycle Sequence Identification

The first gait cycle can be used as a template for finding subsequent gait cycles. For this purpose, a correlation between template (having L samples) and the next L samples could be found. The template is moved across all the remaining samples and a correlation between template and samples is calculated at every step.

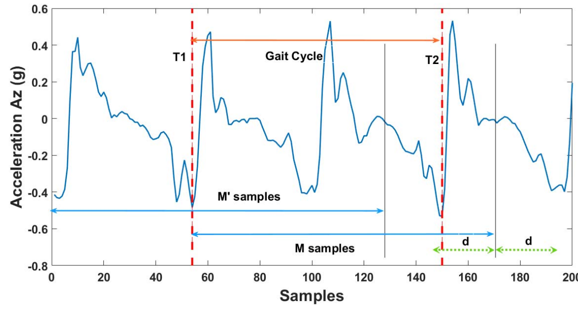

Fig. 3. Gait cycle Identification using local minimums

In this study Pearson Correlation Coefficient (*Pcc*) is used for finding correlation [7]. *Pcc* measures the degree of linear relationship between vectors and its value lies between 1 and -1. A value of 1 represents a perfect positive correlation, a value of -1 represents a negative correlation while a zero value represent no correlation. Figure 4 shows identification of gait cycles and corresponding values of *Pcc*. The peaks of *Pcc* represent a high degree of relationship between template and subsequent cycles and these peaks are used to find out the start and end of subsequent gait cycles.

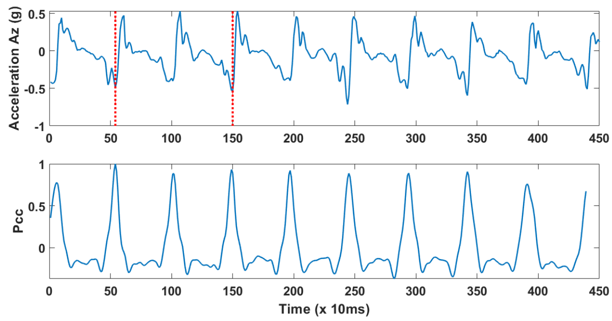

Fig. 4. Gait cycle sequence Identification using correlation

3) Gait Cycles Interpolation

A user walks at various speeds under different scenarios. For example, one may walk slowly while going for a leisure walk or may run if catching a bus. The number of samples for one gait cycle are directly influenced by walking speed. A user walking slowly may have more samples in one gait cycle while a user walking briskly may have less samples per gait cycle. This study uses interpolation to handle variable walking speeds. All the gait cycles are interpolated to have *P* number of samples in every gait cycle (after gait cycle sequence identification). In this study *P* is chosen to be 132, which is the maximum number of samples any subject had in the dataset. So, after the interpolation, all the gait cycles in gait cycle sequence will have 132 samples irrespective of the speed of a user. This facilitates the processing at later stages. This could also be used in future for user authentication since all gait cycles will have same number samples.

B. Features Extraction

The next step after gait cycle sequence interpolation is to extract useful features from these gait cycles which could be used for age estimation and gender classification. Feature extraction is a crucial part of any regression or classification problem. A set of efficient features makes the regression or classification job easier while a poor choice of features makes it difficult. This study uses a set of 30 statistical features for estimation and classification [16]-[17]. Table I gives the details about the features used in this study. Higher order statistical signals including (11) moments and (7) cumulants from 2^{nd} order to 6^{th} order have also been used as features in this study. For feature extraction, all gait cycles are considered as individual signals and features from individual gait cycles are extracted. All signals had 8 gait cycles so 240 features (30 from each gait cycle) were extracted for every subject.

TABLE I. FEATURES USED FOR AGE ESTIMATION AND GENDER CLASSIFICATION

Features	Symbol	Formula
Maximum Amplitude	Smax	max(s(t))
Minimum Amplitude	Smin	min(s(t))
Mean	μ	$1/N \sum s(t)$
Variance	σ^2	$1/N \sum (s(t)-\mu)^2$
Energy	E	$\sum s(t)^2$
Mean of absolute value of 1^{st} derivative	μ^{dx}	$1/N\sum \mid ds/dt \mid$
Mean of absolute value of 2^{nd} derivative	μ^{d2x}	$1/N\sum \mid d^2s/dt^2 \mid$
Peak to peak difference	S_{pp}	Smax – Smin
Maximum latency	L_{max}	t_{smax}/ S_{max}
Minimum latency	L_{min}	t_{smin}/ S_{min}
Peak to peak time	t_{pp}	$L_{smax}+ L_{smin}$
Peak to peak slope	S_{pps}	S_{pp} /t_{pp}
Moments and Cumulants 2nd order to 6th order [17]		

C. Regression and Classification

Classification and regression are performed by various algorithms using the features extracted from gait cycles. Classification algorithms used in this study are Naïve Bayes Classifier, Logistic Regression (LR), Multi-Layer Perceptron (MLP), Support Vector Machine (SVM) and Random Forest (RF) while the regression is performed using Linear Regression, MLP, SVM and RF.

IV. EXPERIMENTS AND RESULTS

All the experiments conducted in this research are conducted using MATLAB and Weka [18]. The first two steps, gait identification and feature extraction have been performed in MATLAB while regression and classification for age estimation and gender classification have been performed using Weka. The algorithms for classification and regression have been used with default settings of Weka. During the experiments, 70% data has been used for training the algorithm and 30% is used for testing the algorithm.

A. Gender Classification

Gender classification is performed using Naïve Bayes, LR, MLP, SVM and RF classifiers in Weka. The performance evaluation parameters and the experimental results of gender classification are discussed in this section.

1) Performance Evaluation Parameters

True positive rate (recall) for male and female subjects and classification accuracy (*CA*) have been used as evaluation parameters. The formulae for these are given below.

True Positive Rate (Recall) for Male or Female =

Number of male or female subjects correctly classified /

Total Number of male or female subjects

Classification Accuracy (CA) = Correctly classified subjects / Total subjects

Here recall represents the number of correctly classified samples for a class (male/female) out of total samples for that class and *CA* is overall accuracy including both male and female classes.

2) Results and Analysis

Table II shows the results of gender classification for sequence (seq) 0 and sequence (seq) 1.

TABLE II. GENDER CLASSIFICATION RESULTS

Method	Recall Male (%)	Recall Female (%)	Accuracy (%)
Results for Walk Sequence 0			
Naïve Bayes	75.7	28.7	52.9
Logistic Regression	**72.2**	**63.9**	**68.2**
Multi-Layer Perceptron	31.3	79.6	54.7
Support Vector Machine	83.5	28.7	57.0
Random Forest	57.4	63.9	60.5
Results for Walk Sequence 1			
Naïve Bayes	42.6	63.0	52.4
Logistic Regression	**66.1**	**63.9**	**65.0**
Multi-Layer Perceptron	10.4	91.7	49.8
Support Vector Machine	63.5	48.1	56.1
Random Forest	60.9	63.0	61.9

The best performance is shown by LR classifier with a *CA* of 68.2% for seq 0 and 65% for seq 1. The performance of LR classifier is equally good for male and female categories as shown by recall results for male and female. The second-best performance after LR is achieved by RF with an accuracy of 60.5% and 61.9% for seq 0 and seq 1 respectively. All other methods showed a very poor overall accuracy and most of the methods showed biasness towards either male or female accuracy with an unbalanced recall for male and female.

Moreover, the results for seq 1 are poor for most of the methods compared seq 0 which shows that seq 1 data is probably more difficult to classify.

B. Age Estimation

Age estimation is performed using Linear regression, MLP, SVM and RF in Weka. The performance evaluation parameters and the experimental results of age estimation are discussed in this section.

1) Performance Evaluation Parameters

The following parameters are used for comparing the performance of the regression algorithms; Correlation coefficient (CC) [7],[18], Mean absolute error (MAE) and Root mean square error (RMSE) [16]. The formulae and explanation of all these parameters is given in corresponding references. The value of CC close to 1 shows a highly positive correlation between predicted and actual age, a value close to -1 shows a highly negative correlation while a value close to zero shows poor relation. A high value of MAE and RMSE shows a greater difference between the actual and predicted age.

2) Results and Analysis

Table III shows the results of age estimation for seq 0 and seq 1. The best performance for both sequences is shown by RF method with correlation coefficient, MAE and RMSE of 0.57, 12.6 and 14.4 for seq 0 and 0.55, 12.1 and 14.3 for seq 1 respectively. SVM although showed a better performance than RF for seq 0 with lower MAE and RMSE, it showed extremely poor performance for seq 1. The performance of all other methods was poor and only Linear Regression showed decent performance. Most of the methods performed poorly for seq 1 compared to seq 0.

TABLE III. AGE ESTIMATION RESULTS

Method	**Correlation Coefficient**	**MAE**	**RMSE**
Results for Walk Sequence 0			
Linear Regression	0.47	13.1	17.3
Multi-Layer Perceptron	0.30	13.6	16.2
Support Vector Machine	**0.57**	**11.6**	**14.0**
Random Forest	0.57	12.6	14.4
Results for Walk Sequence 1			
Linear Regression	0.51	12.6	16.5
Multi-Layer Perceptron	0.19	16.8	27.7
Support Vector Machine	0.07	24.0	184.0
Random Forest	**0.55**	**12.1**	**14.3**

In addition to the results achieved using Weka, age estimation using artificial neural network with 10 neurons and Levenberg-Marquardt training algorithm was also performed in MATLAB for comparison. The results showed a much better performance compared to the performance achieved using Weka. The value of R and RMSE were 0.69 and 10.54 for seq 0 respectively. The results for seq 1 were also much better compared to the results achieved using Weka. This shows that the proposed method has the potential to produce better results but more algorithm tests need to be performed for evaluating the effectiveness and robustness of the proposed method.

V. CONCLUSIONS

This paper proposes a method for age estimation and gender classification using human gait cycle. The largest inertial sensors based human gait database comprising of 744 subjects with a balanced distribution of male and female subjects is used in this study. The human gait cycles are identified using accelerometer signals captured through sensors attached to human body. Features are extracted from gait cycles, and gender classification and age estimation is performed by using these features in machine learning algorithms. Experiments are performed on two different walk sequences and the results show the effectiveness of the proposed method for gender classification and age estimation. The best performance for gender classification was achieved by logistic regression while for age estimation random forest showed the best results.

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