Expert Systems With Applications 93 (2018) 257–266

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Gender classification in smartphones using gait information

Ankita Jain, Vivek Kanhangad*

Discipline of Electrical Engineering, Indian Institute of Technology Indore, Indore 453 552, India

A R T I C L E I N F O

Article history:
Received 19 October 2016
Revised 5 October 2017
Accepted 6 October 2017
Available online 9 October 2017

Keywords:
Gait biometrics
Gender recognition
Accelerometer
Gyroscope
Histogram of gradient

A B S T R A C T

Gender classification in smartphones has a lot of potential applications. Specifically, the gender information can be used by expert and intelligent systems that are part of healthcare, smart spaces and biometric-based access control applications. For example, operations of intelligent systems in a smart space can be customized based on gender information to provide an enhanced user experience. Similarly, a biometric system can use gender as a soft biometric trait to improve its user authentication performance. This paper presents an approach for gender classification using users' gait information captured using the built-in sensors of a smartphone. Histogram of gradient (HG) method is proposed to extract features from the gait data, which includes a set of signals collected from accelerometer and gyroscope sensors of a smartphone. The bootstrap aggregating classifier utilizes the discriminatory information in these features for classification of the gender. The performance of the proposed approach has been evaluated on datasets collected using two different smartphones. These datasets contain a total of 654 gait data from 109 subjects. Our experimental results show that the classification accuracy of the proposed approach is higher than that of the existing methods. Additional experiments performed to examine the effect of variations in walking speed indicate that these variations have a minimal impact on the performance of proposed approach. Furthermore, results from our experiments performed on the gait data collected using two different smartphones suggest that the performance of the proposed algorithm for gender recognition is consistent across the two datasets, achieving classification accuracies of 91.78%, 94.44% and 88.89% on the first dataset and 90.48%, 91.07% and 88.46% on the second dataset for normal, fast and slow walking speeds, respectively. The results of this study are significant as they indicate that gait information captured by the smartphones' built-in sensors can be used to derive gender information reliably and unobtrusively.

1. Introduction

Providing biometric-based intelligence for smartphones has been a topic of great interest to researchers across multiple areas. One such intelligence, which can be used in various applications to improve the user experience, is classification or recognition of the gender of a smartphone user based on user's gait data collected from the smartphone's built-in sensors such as accelerometer and gyroscope. In addition, the gender information can be used in pervasive computing applications. For example, the information can be communicated to devices embedded in the smart space to adjust intensity and color of the lighting in a room based on general preferences of the identified gender. Gender information can also be utilized by access control systems in smart spaces, where only a particular gender (male or female) is allowed to enter. Additionally, user authentication accuracy can also be improved by combining traditional biometric information with soft biometrics like gender, age, height, weight, and ethnicity. Such soft biometric attributes can be used in various applications such as surveillance, biometric authentication, demographic analysis, access control, marketing and human-machine interactions. Humans can easily identify gender of the user by looking at face, analyzing the style of walking or listening to the speech. However, it is still a challenging task to completely automate gender classification (Ng, Tay, & Goi, 2012) using user's biometric data.

The rest of the paper is organized as follows: related work is discussed in Section 2. A detailed description of the proposed approach for gender recognition is presented in Section 3. Section 4 presents details about the gait dataset collected using smartphones. This section also presents experimental results and discussion. Finally, conclusion and future research directions are presented in Section 5.

* Corresponding author.
E-mail addresses: phd1301202001@iiti.ac.in (A. Jain), kvivek@iiti.ac.in (V. Kanhangad).

https://doi.org/10.1016/j.eswa.2017.10.017
0957-4174/

2. Related work

Researchers have explored gender classification using face (Chen & Ross, 2011; Danisman, Bilasco, & Martinet, 2015; Lu, Chen, & Jain, 2005), speech (Agneessens, Bisio, Lavagetto, & Marchese, 2010; Bisio, Delfino, Lavagetto, Marchese, & Sciarrone, 2013) and video-based gait (Hu, Wang, Zhang, & Zhang, 2011; Li, Maybank, Yan, Tao, & Xu, 2008; Lu, Wang, & Moulin, 2014) biometrics. Chen and Ross (2011) utilized near-infrared and thermal face images for gender classification. The authors used histogram of the local binary patterns as features and different classifiers such as SVM, kNN, Adaboost. Lu et al. (2005) identified gender and ethnicity by consolidating the range and intensity information from facial scans. Danisman et al. (2015) proposed a fuzzy inference based gender classification approach, which utilizes hair volume, mustache, and information from a vision-sensor. Researchers have also investigated ear (Gnanasivam & Muttan, 2012), fingerprint (Li, Zhao, Fu, & Liu, 2010), hand geometry (Wu & Yuan, 2014) and iris (Thomas, Chawla, Bowyer, & Flynn, 2007) biometrics for gender identification.

Vision-based gait biometrics has also been employed to classify gender. Hu et al. (2011) have employed shape descriptor for spatial information and periodic shape variations for temporal information. Li et al. (2008) developed an algorithm to obtain gait information from motions of the different parts of silhouette. Lu et al. (2014) investigated arbitrary walking directions to recognize the identity and gender of human. Igual, Lapedriza, and Borras (2013) and Kastaniotis, Theodorakopoulos, Economou, and Fotopoulos (2013) classified the gender by using gait data captured from depth camera. Igual et al. (2013) have proposed a fast feature extraction algorithm that considers 3D point cloud obtained from gait image sequences. Kastaniotis et al. (2013) developed a method in which motion of frames is encoded using an angular representation.

A comprehensive review of biometrics-based gender recognition is available in Ng et al. (2012) and Yu, Tan, Huang, Jia, and Wu (2009). Researchers have also performed combination of multiple biometric traits for gender classification (Li et al., 2010; Shan, Gong, & McOwan, 2008; Zhang & Wang, 2009). Li et al. (2010) have employed fusion of face and fingerprint for gender recognition. Authors in Shan et al. (2008) and Zhang and Wang (2009) have performed gender classification using face and gait. In biometrics, user authentication accuracy can be enhanced by integrating the gender information with conventional biometric traits (Jain, Nandakumar, Lu, & Park, 2004; Park & Jain, 2010). Jain et al. (2004) achieved better authentication performance when soft biometrics information such as gender, height, and ethnicity incorporated with face and fingerprint biometrics.

Over the last decade, the use of smartphones has increased rapidly. Currently, smartphones play a significant role in our everyday life. Therefore, researchers have also focused their efforts for developing several applications including smartphone-based healthcare systems (Minutolo, Esposito, & Pietro, 2015). Ogunduyile, Zuva, Randle, and Zuva (2013) and Ren, Chen, Chuah, and Yang (2015) utilized the built-in sensors of mobile phone for diagnosis, remote monitoring and to provide advice to patients. Ren et al. (2015) also utilized the built-in sensors to detect spoofing in mobile healthcare systems. Minutolo et al. (2015) proposed an innovative and efficient decision support system to provide remote health monitoring. They also showed the effectiveness of the system in real-time conditions on mobile devices. Incorporating the gender information into mobile healthcare systems can enable gender-specific medical advice to the patients, especially in smartphone-based remote medical advice services. Furthermore, gender information in smartphones can be used to improve the interaction of user with the device (Miguel-Hurtado, Stevenage, Bevan, & Guest, 2016). Specifically, gender classification can be used to provide better search results for shopping, themes, new applications to the smartphone user. Another potential application is the targeted advertisement, in which advertisements can be recommended based on user's gender (Wang, Tang, Ma, & Qin, 2015). As reported by a study (Vergeest, 2013), women are more concerned about their safety and use their phones more for safety purposes as compared to man. The existing mobile applications on women safety can also utilize the gender information to improve its safety features.

Generally, gender classification in mobile phones is performed by employing either visual or audio signal. Agneessens et al. (2010) employed audio signal collected by phone to classify the gender. Authors also identified the number of speakers and their gender by utilizing speech signals. More recently, Choi, Kim, Kim, Park, and Park (2016) have proposed a method for prediction of mobile users' gender using text message data. Gender recognition has also been performed using users' keystroke dynamics and swipe gestures captured from touchscreen-based mobile phones (Antal & Nemes, 2016; Miguel-Hurtado et al., 2016). Antal and Nemes (2016) have achieved gender classification accuracy of 64.76% and 57.6% using keystroke dynamics and swipe gestures, respectively. Miguel-Hurtado et al. (2016) have applied a feature selection technique to a set of 14 features extracted from the captured swipe gesture. Their approach achieves gender classification accuracy of 78.2%.

Several approaches have also been proposed for user authentication based on gait biometrics captured using wearable sensors (Thang, Viet, Thuc, & Choi, 2012; Zhang et al., 2015; Zhong & Deng, 2014). Zhang, Pan, Jia, Lu, Wang, and Wu (2015) proposed an approach for user authentication by capturing gait information from wearable accelerometer sensors placed at various positions of the human body. Thang et al. (2012) employed only accelerometer sensor of smartphone for user authentication while Zhong and Deng (2014) utilized gait information captured from both accelerometer and gyroscope sensors of smartphone for user authentication.

Weiss and Lockhart (2010) identified soft biometrics traits such as height, weight, and gender by extracting 43 statistical features from built-in accelerometer sensor readings of a phone. They employed different classifiers from the Weka data mining tool (Hall et al., 2009), particularly, instance-based learning, J48 decision tree and multilayer neural network. However, their study is limited to gait information obtained only from the accelerometer sensor. In a more recent work (Jain & Kanhangad, 2016), the combination of information captured by the accelerometer and gyroscope sensors of smartphone has been investigated for gender recognition. The results presented in Jain and Kanhangad (2016) suggest that the combination of information collected by the two sensors results in improved performance for gender classification. However, the performance of gait based gender recognition in smartphones needs to be improved significantly before it can be incorporated into mobile phone-based healthcare services or other real-world applications. Table 1 shows a summary of the existing methods for mobile phone-based gender recognition. In this table, ACC stands for the classification accuracy.

The objective of this work is to develop an approach to reliably identify the gender by utilizing gait data acquired from the built-in sensors of smartphones. The motivation behind choosing gait is that it can be captured unobtrusively without any conscious effort from the user. The key contributions of our work are as follows:

(1) A novel approach for classification of gender of a smartphone user using the proposed histogram of gradient (HG) features. Since this work does not utilize any visual informa-

Table 1
A summary and comparison of the existing methods for gender classification in mobile phones.

Study	Modality	Methodology	Number of subjects in the dataset	Best performance	Remarks
Agneessens et al. (2010)	Speech	Mean of probability distribution function with predefined threshold	1 male and 1 female	ACC: 90%	(i) Suited for telephone-based applications (ii) Evaluated on a small dataset
Choi et al. (2016)	Text data	Based on similarities between the text data and the word-set of each gender	16 males and 16 females	F-score: 0.87	(i) Requires less computation (ii) Some of the words cannot be classified into either category, i.e., unclassified cases (iii) In some languages, the texts used by the male and female users are subtle
Antal and Nemes (2016)	Keystroke	A set of 71 features with random forests classification	18 males and 18 females	ACC: 64.76%	(i) No risk of privacy of users (ii) User needs to type password or perform gestures (iii) The performance is not very promising, therefore it does not seem a reliable way to classify gender
	Swipe gestures	A set of 9 features with random forests classification	38 males and 38 females	ACC: 57.16%	
Miguel-Hurtado et al. (2016)	Swipe gestures	A set of 14 features with multilinear logistic regression classifier	57 males and 59 females	ACC: 78.2%	
Weiss and Lockhart (2010)	Gait	A set of statistical features with NN, IB3 and J48 classifiers	38 males and 28 females	ACC: 71.2%	(i) Can be performed unobtrusively (ii) Data from only the accelerometer sensor is employed (iii) Evaluated on a small dataset (iv) Variations in walking speed are not considered
Jain and Kanhangad (2016)	Gait	Multi-level local pattern-based features with bagging classifier	25 males and 17 females	ACC: 77.45%	(i) Can be performed unobtrusively (ii) Readings from both accelerometer and gyroscope sensors are explored (iii) Evaluated on a small dataset (iv) Different walking speeds are considered but no cross-speed experimental results

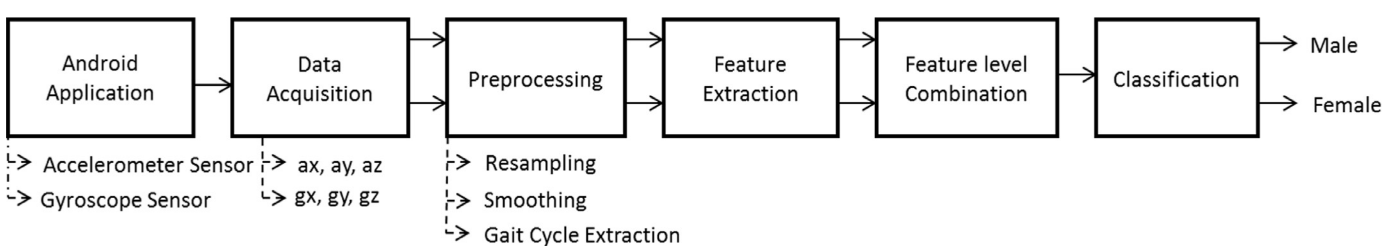

Fig. 1. Block diagram of proposed approach for gender recognition.

tion, we have reformulated the histogram of oriented gradients (HOG) (Dalal & Triggs, 2005) to devise the HG descriptor for one-dimensional (1D) signals. The difference between the HOG and the proposed HG descriptor is explained in Section 3.3.

(2) The proposed work explores the combination of gait information collected from accelerometer and gyroscope sensors for gender recognition in smartphones.
(3) A total of 654 gait data is acquired from 109 subjects using smartphone sensors with variations in walking speed. The gait data is collected using two different devices to ascertain the gender recognition accuracy of the proposed approach.

3. Proposed method

The block diagram of the proposed approach for gender classification is shown in Fig. 1. The android application collects the gait biometrics of the user. Specifically, readings from built-in accelerometer and gyroscope sensors of smartphone are recorded with the help of this application. The accelerometer and gyroscope sensor readings in *x*,*y* and *z* directions constitute the gait data, which are preprocessed for resampling and low pass filtering in the time domain. In the next stage, features are extracted from the gait data. Finally, the discriminatory features extracted from accelerometer and gyroscope sensor readings are combined to obtain the final feature representation, which is fed to a binary classifier for classification of the user's gender.

3.1. Data acquisition

The android application captures the accelerometer and gyroscope sensor readings of the user's gait in *x*, *y* and *z* directions of the smartphone. Accelerometer sensor provides the amount of linear acceleration on the phone in *x*, *y* and *z* directions. Fig. 2 shows these directions and typical accelerometer readings of the user's gait captured by the android application.

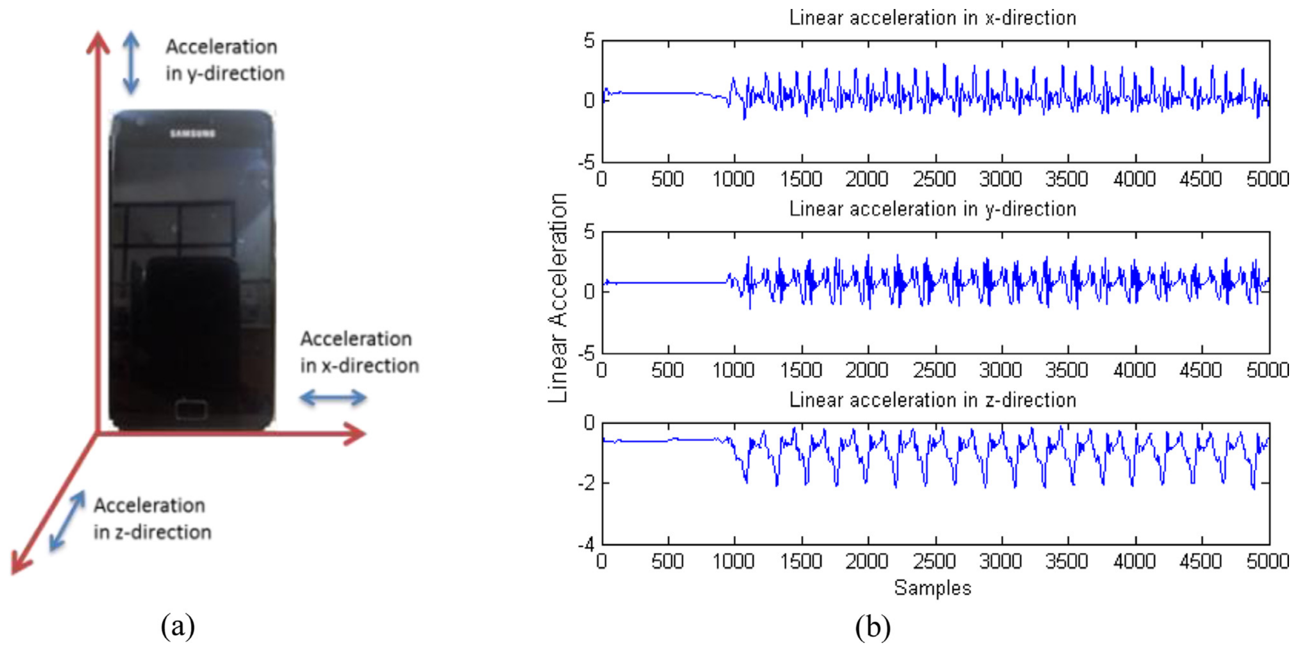

Fig. 2. Accelerometer sensor readings: (a) *x*, *y* and *z* directions defined relative to the smartphone and (b) linear acceleration signals.

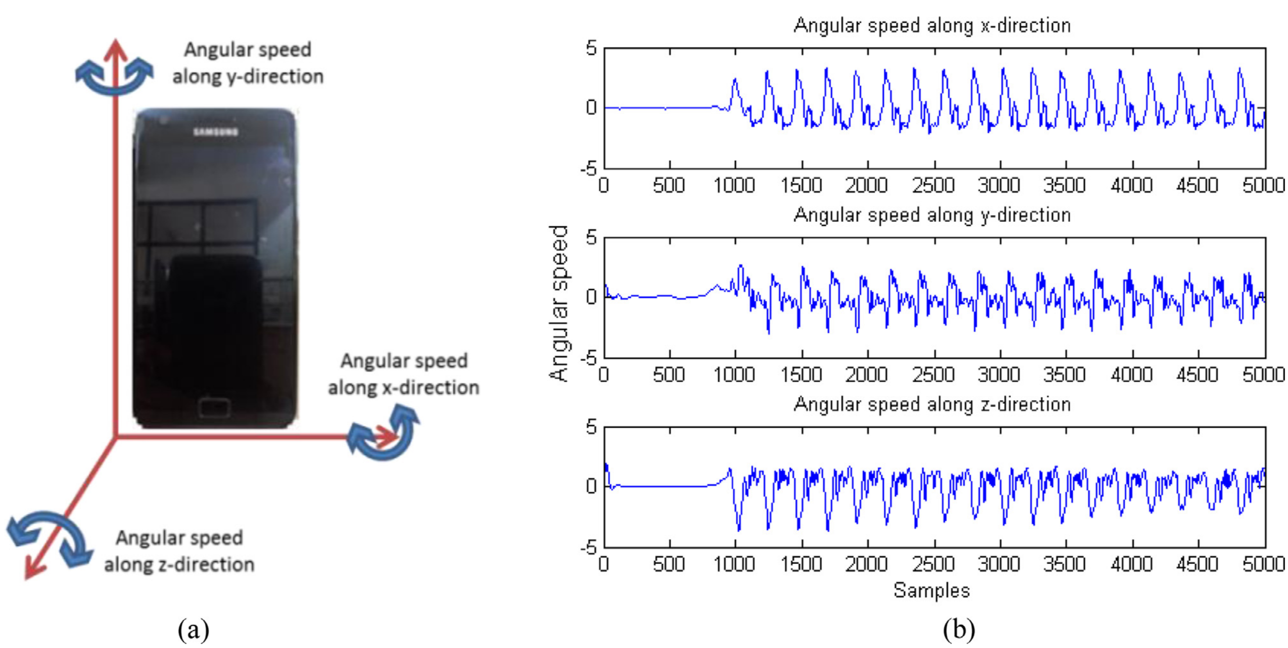

Fig. 3. Gyroscope sensor readings: (a) *x*, *y* and *z* directions defined relative to the smartphone and (b) angular speed signals.

On the other hand, gyroscope sensor measures angular speed exerted on the phone by the user along *x*, *y* and *z* directions. Fig. 3 shows these directions and typical gyroscope readings of the user's gait captured by the android application.

3.2. Preprocessing

3.2.1. Normalization

The accelerometer and gyroscope sensor readings are normalized to have zero mean and unit standard deviation (Zhong & Deng, 2014). Since the sampling rate of the signals captured by the application from accelerometer and gyroscope sensors is not fixed, it is necessary to resample the signal at a fixed sampling rate before further processing. In this work, these signals are resampled at a fixed sampling rate of 100 Hz by using cubic spline interpolation. This is followed by moving average filtering of the signals to reduce noise.

3.2.2. Gait cycle extraction

As can be seen in Fig. 4, human gait signals generally exhibit periodically repeating patterns with multiple gait cycles. However, the gait cycles in the recorded gait data may vary with time because of many reasons including variations in walking speed of the user and irregular walking behavior. Majority of the existing techniques for gait cycle extraction utilize accelerometer sensor reading in only one direction. However, our preliminary experiments indicated that such an approach might not provide accurate gait cycles. Therefore, in this work, we have developed a heuristic technique to extract gait cycles using sensor readings in all the three directions. Our approach primarily relies on accelerometer signal

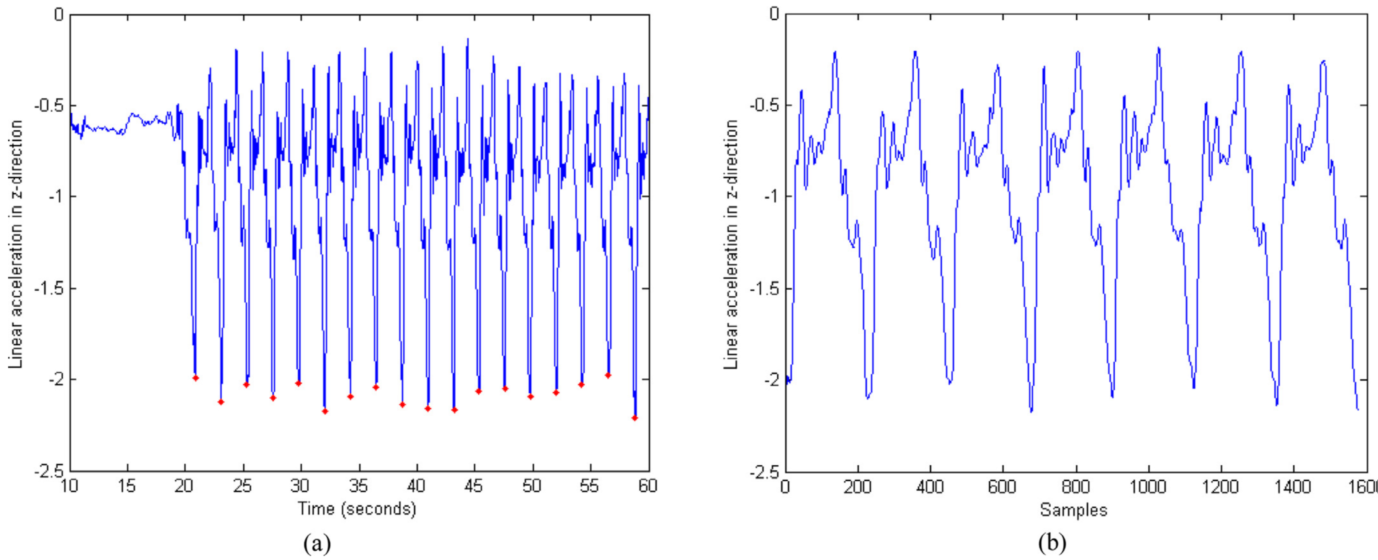

Fig. 4. (a) Local minima points of accelerometer signal in z- direction and (b) the extracted gait cycles.

in the z-direction for identifying local minima points, which help us in extracting gait cycles. Specifically, a point is considered to be local minimum if the value of the current sample is less than that of its neighboring samples and their differences are higher than a threshold. These local minima points are refined using accelerometer signals in x and y directions. Specifically, only those points that have corresponding local minima points (within a small neighborhood of 0.5 s) in accelerometer signals in x and y directions are considered for extracting gait cycles. Fig. 4(a) shows the local minima points computed for linear acceleration signal in z- direction, in which the set of sample points between two consecutive minima constitute one gait cycle. In our experiments, a total of seven such gait cycles are extracted for further processing. However, we have also performed a set of experiments to study the effect of the number of gait cycles on the gender recognition performance, results of which are presented in Section 4.4. Fig. 4(b) shows gait cycles extracted from the accelerometer sensor signal in z- direction. Similarly, gait cycles from the rest of the signals - accelerometer sensor signals in x and y directions and gyroscope sensor signals in x, y and z directions are extracted by considering the sample points that correspond to those constituting the gait cycles extracted from accelerometer sensor signal in the z- direction.

3.3. Feature extraction

The proposed approach for gender classification employs a novel feature extraction technique, which is based on the histogram of oriented gradients (HOG) proposed by Dalal and Triggs (2005). The HOG was originally proposed for human detection in images. Due to its excellent performance, HOG and its variants have been successfully employed for numerous computer vision applications including face recognition (Albiol, Monzo, Martin, Sastre, & Albiol, 2008), character recognition (Su, Lu, Tian, Lim, & Tan, 2014), traffic sign recognition (Berkaya, Gunduz, Ozsen, Akinlar, & Gunal, 2016) and video surveillance system (Arroyo, Yebes, Bergasa, Daza, & Almazán, 2015). Besides these applications, HOG descriptors have also been utilized to recognize gender from still images of body parts (Cao, Dikmen, Fu, & Huang, 2008). In this work, we develop a one-dimensional (1D) version of the HOG descriptor. Since gradients are oriented in only one direction in a 1D signal, we refer to the modified descriptor as the histogram of gradients (HG). Fig. 5 shows the computational stages involved in the proposed feature extraction technique. Details of each of these stages are presented in the following sub-sections.

3.3.1. Computation of gradients

The first step in the proposed feature extraction process is to compute the gradient and the angle of gradient. For discrete signals, gradients can be estimated using different masks. In this work, we have explored the following masks (Dalal & Triggs, 2005) for computation of gradients: centered $[-1,0,1]$, uncentered $[-1,1]$ and cubic-corrected $[1,-8,0,8,-1]$.

3.3.2. Histogram binning

The key processing stage in the proposed feature extraction technique is the histogram binning, which generates a gradient-based histogram feature. In this stage, the gait cycle is divided into six non-overlapping cells and a histogram for each cell is computed using the gradient and the angle of gradient. The range of gradient angle (0° - 180°) is divided uniformly to generate six histogram bins (Dalal & Triggs, 2005). Fig. 6 shows an example of a cell histogram computed using the gradient and angle of gradient. A bin for each element of the cell is identified using its gradient angle and it is voted with the gradient value of the element. This process is repeated for every element of the cell to generate a cell histogram.

3.3.3. Block normalization

The cell histograms computed in the previous stage are normalized by considering a group of cells or a block. In this work, overlapping blocks consisting of two cells are considered. This generates five overlapping blocks for a gait cycle with six cells. The cell histograms of a block can be normalized using various methods and we have explored L_1-norm, L_1-sqrt and L_2-norm based normalization techniques, which are defined as follows (Dalal & Triggs, 2005):

(a) L_1-norm:

$$H_N = \frac{H}{(\|H\|_1 + \epsilon)} \tag{1}$$

(b) L_1-sqrt:

$$H_N = \sqrt{\frac{H}{(\|H\|_1 + \epsilon)}} \tag{2}$$

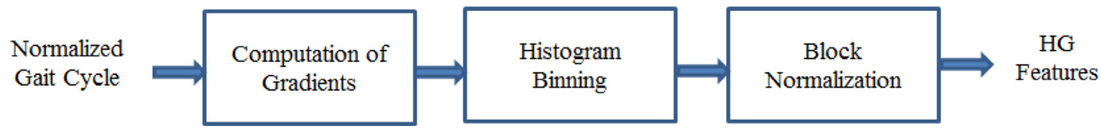

Fig. 5. Overview of the proposed feature extraction method.

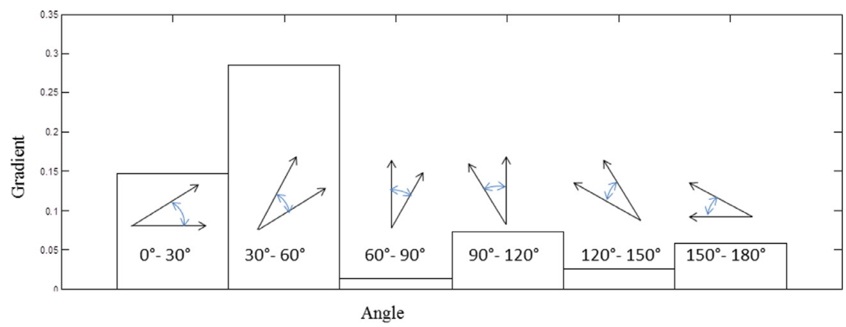

Fig. 6. Generation of HG descriptor.

(c) L_2-norm:

$$H_N = \frac{H}{\sqrt{(\|H\|_2^2 + \epsilon^2)}} \tag{3}$$

where H is the histogram generated by concatenating two cell histograms in a block, H_N is the corresponding normalized histogram and ϵ is a very small constant. The above-described normalization process generates five normalized histograms for each gait cycle, which are concatenated to form the HG descriptor of length 60. Finally, the normalized histograms corresponding to seven gait cycles are concatenated to form a feature vector of length 420 for a gait signal.

3.4. Feature level combination

As discussed in the previous section, the proposed approach generates a histogram feature of length 420 for each of the gait signals acquired from accelerometer and gyroscope sensors in x, y and z directions. Therefore, there is a need for efficient combination of this information. Broadly, information fusion can be performed in two ways namely, pre-classification fusion and post-classification fusion. Jain, Nandakumar, and Ross (2005) observed that pre-classification fusion is expected to perform better than post-classification fusion. Therefore, in the proposed work, information fusion is performed at feature level (pre-classification) by concatenating the normalized histograms to obtain the final representation. In our case, the pre-classification information fusion can be represented as:

$$H_{Ncat} = [H_{N1} H_{N2} H_{N3} \ldots . H_{Nn}] \tag{4}$$

where, H_{N1}, H_{N2}, H_{N3}, ..., H_{Nn} are the histogram features and H_{Ncat} is the concatenated histogram. In Eq. (4), individual histogram features (of length 420) that are computed from accelerometer and gyroscope sensor readings in x, y and z directions are concatenated to form the final feature representation of length 2520.

3.5. Classification

Bootstrap aggregating (Breiman, 1996), also known as bagging, is designed to provide stable and improved performance for machine learning algorithms used for classification and regression. It is an ensemble method in which multiple predictors are aggregated. It trains an ensemble of decision trees either for classification or regression using bootstrap method. Specifically, it generates an aggregated predictor by using multiple versions of a predictor, which are created by training the base predictor on bootstrap replicates of the training set. Finally, bagging generates an aggregated model by combining the outputs of the individual models using plurality voting in the case of classification.

4. Experimental results and discussion

4.1. Data acquisition

We have developed an android application on IntelliJ platform to acquire users' gait information. The application captures accelerometer and gyroscope sensor readings in x, y and z directions of the device, which we collectively refer to as gait data. We have employed two devices namely, Samsung Galaxy S-II GT-I9100 (S-II) and Note-II N7100 (N-II) for collection of gait data. A total of 109 subjects participated in the data collection process. These subjects were instructed to keep the device in the front pocket of their trouser and to walk in a straight path. To collect gait data corresponding to different walking speeds, subjects were instructed to walk at (what they think is) normal, fast and slow walking speeds. This process was repeated twice, collecting six gait data from each subject. Therefore, our dataset consists of a total of 654 gait data acquired from 109 subjects.

4.2. Experiments with S-II device

The S-II device was used to collect gait data from 46 subjects, out of which 25 were male and 21 were female subjects in the age range of 19 and 36 years. This subset of our dataset consists of 276 gait data.

Initially, we have performed experiments to evaluate individual performances of accelerometer and gyroscope sensor readings for gender identification. In this set of experiments, we have used the 5-fold cross-validation methodology and ensured that no overlap of subjects existed between our training and testing datasets. This is ensured by partitioning the dataset in such a way that all gait data from a subject is grouped into a single partition. Specifically, gait data belonging to 25 male subjects are equally divided to generate 5 partitions, with each partition containing 5 male subjects' gait data. Similarly, gait data belonging to 20 female subjects are distributed equally into five partitions and the remaining gait data belonging to a female user is considered to be part of one of the five partitions. In this way, four partitions for the 5-fold cross-

Table 2
Comparison of individual performance of gait information collected from accelerometer and gyroscope sensors with the combined performance for gender classification.

Walking speed	Gait information		
	Accelerometer	Gyroscope	Accelerometer ++ Gyroscope
Normal	78.56%	81.67%	91.78%
Fast	81.11%	80%	94.44%
Slow	83.33%	70.83%	88.89%

Table 3
Cross-speed gender classification accuracy on gait dataset collected using S-II device.

Train\Test	Normal	Fast	Slow
Normal	93.18%	92.22%	92.04%
Fast	92.39%	95.45%	88.64%
Slow	89.13%	85.56%	92.86%

validation contain gait data belonging to 5 male and 4 female subjects and the fifth partition contains gait data belonging to 5 male and 5 female subjects.

Our preliminary experiments indicated that the centered mask with L_1-norm based normalization provides better performance than other combinations of gradient computation and histogram normalization techniques for gender classification. Therefore, we have employed the above techniques for further analysis. The average 5-fold cross-validation accuracy of the proposed approach on this dataset is presented in Table 2. It can be observed from the table that the performance of gender classification using gait data collected from gyroscope sensor is comparable with that of the approach based only on the accelerometer sensor readings, except for the case when subjects walked at slow pace. This observation motivated us to explore the combination of information from gyroscope and accelerometer sensor readings to further improve the gender classification accuracy. We have performed pre-classification fusion by concatenating the two HG descriptors derived from accelerometer and gyroscope sensors readings. The accuracy of the gender classification approach which combines information from accelerometer and gyroscope sensors is presented in the last column of Table 2. It can be seen that the gender classification approach based on the combination of information from accelerometer and gyroscope sensors clearly outperforms the one based on either accelerometer or gyroscope sensors. Therefore, it can be concluded from this set of experiments that in addition to accelerometer sensor readings, gyroscope sensor readings also provide the discriminatory information for gender recognition and their feature level combination leads to significant improvement in classification accuracy.

We have also performed a set of experiments, which considers more realistic scenarios. It is very unlikely that a user walks at the same speed all the time. Therefore, ideally, the performance of gender classification approach should not be affected by variations in the user's walking speeds. To evaluate the performance of the proposed approach under such scenarios, we have performed experiments with training and testing sets consisting of gait data corresponding to different walking speeds, which we refer to as cross-speed gender classification. The experimental results from this set of experiments are presented in Table 3. In all these experiments, we have partitioned the dataset into training and testing sets, which contain all users' gait data corresponding to a specific category. However, for normal versus normal, fast versus fast and slow versus slow cases, gait data belonging to 50% of the users is used for training, while the rest of the gait data is used for testing, which ensures that there is no overlap of users between training and testing sets. It can be observed from Table 3 that the performance deterioration for cross-speed cases is only marginal, except for the cases such as slow versus fast and fast versus slow. This is possibly due to significant change in the walking speeds between the training and testing sets for those cases.

To analyze why the HG features are effective for gender classification, we have identified the top 3 features in the proposed HG based feature vector and plotted a scatter diagram. The complete set of gait data corresponding to normal walking speed collected using S-II device is used for this purpose. We have employed the Fisher score based feature selection technique (Duda, Hart, & Stork, 2001), which assigns a rank to each feature based on its discriminative capability, to identify the top 3 features. Fig. 7 shows the scatter diagram, which helps us visualize the discriminative capability of these features. As can be seen in this figure, the majority of data points corresponding to male and female subjects are well separated in the three-dimensional feature space. In the original feature space, the separation between the two clusters of data points belonging to male and female subjects is expected to improve further due to the inclusion of additional features. This possibly explains why the proposed features are effective for gender classification using gait data.

Table 4
Comparison of individual performance of gait information collected from accelerometer and gyroscope sensors with the combined performance for gender identification.

	Gait information		
Walking speed	Accelerometer	Gyroscope	Accelerometer ++ Gyroscope
Normal	85.59%	76.08%	90.48%
Fast	85.13%	76.68%	91.07%
Slow	78.53%	71.39%	88.46%

4.3. Experiments with Note-II device

In this section, we present results from a set of experiments carried out to evaluate the performance of the proposed approach on a dataset collected using a different device. The key objective of this experiment is to ascertain the performance of the proposed gender classification approach and to investigate if the device used for data collection has any impact on its performance. As described in Section 4.1, we have employed Note-II device to collect gait data from 63 subjects. Out of 63 subjects, 33 were male and 30 were female subjects aged between 20 and 33 years. The two sets of subjects (who participated in experiments with S-II and Note-II devices) are disjoint. Six gait samples with variations in walking speed (slow, normal and fast) are acquired from each subject. Therefore, this dataset contains a total of 378 gait data.

In the first set of experiments, effectiveness of features extracted from accelerometer and gyroscope sensor readings are investigated separately. In addition, we have also explored the feature-level combination of accelerometer and gyroscope sensor readings. In these experiments, we have used 5-fold cross-validation methodology and partitioned the dataset in such a way that no overlap of subjects existed between the five subsets. Specifically, we have created five subsets, with each subset containing gait data of 6 male and 6 female subjects. The gait data belonging to remaining 3 male subjects are distributed into three different subsets. The average 5-fold classification accuracies from this set of experiments are presented in Table 4. It can be observed that the classification accuracies presented in Tables 2 and 4 are comparable and therefore the performance is consistent across the two gait datasets. The results presented in Table 4 further demonstrate that gyroscope sensor readings are useful for gait based gen-

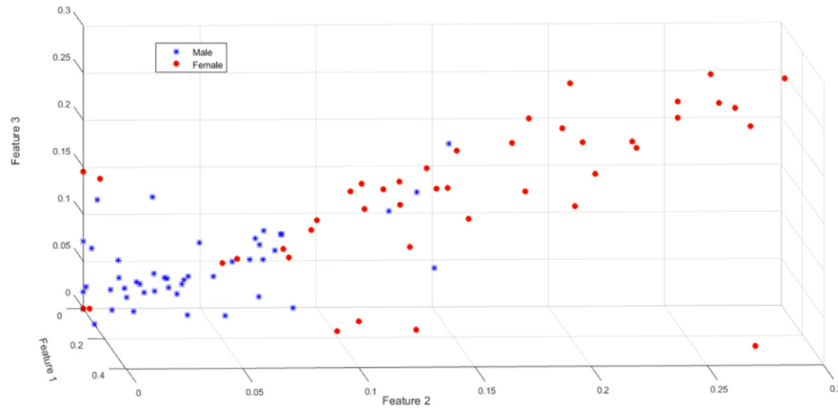

Fig. 7. Scatter diagram of the top three features determined using Fisher score based feature selection method.

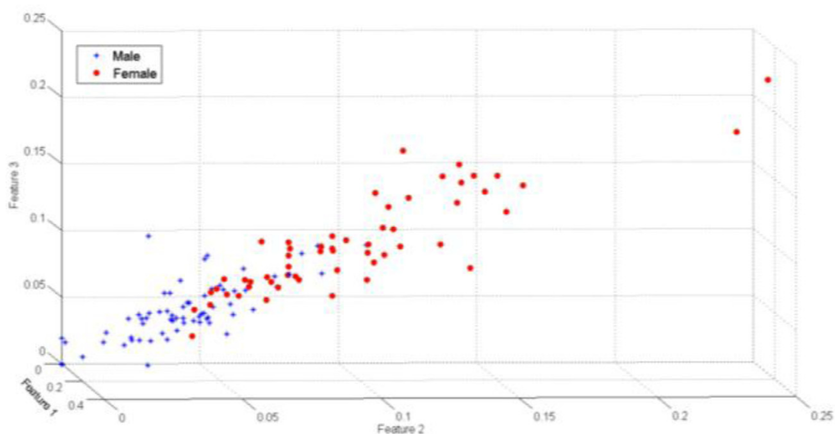

Fig. 8. Scatter diagram for the top three features determined using Fisher score based feature selection method.

Table 5
Cross-speed gender classification accuracy on gait dataset collected using Note-II device.

Train\Test	Normal	Fast	Slow
Normal	93.33%	88.33%	87.72%
Fast	90.98%	91.67%	80.70%
Slow	83.61%	70.83%	87.50%

der recognition in mobile phones. As expected, the combination of information from accelerometer and gyroscope sensor readings results in significant improvement in classification accuracy.

In the second set of experiments, we have considered cross-speed gender classification scenarios. We have followed the same experimental protocol as the one adopted for cross-speed experiments described in Section 4.2. The experimental results are summarized in Table 5. The key observation in this table is that the performance trend remains the same as in the first dataset. Specifically, there is slight deterioration in the classification accuracy for majority of the cross-speed cases presented in Table 5. However, the performance deterioration is significant for fast versus slow and slow versus fast scenarios, indicating that the proposed approach may not be very effective when there is significant change in walking speeds between training and testing data.

In order to visualize the effectiveness of the proposed HG features on this dataset, the top 3 features in the HG based feature vector have been determined using Fisher score based feature selection technique (please refer to Section 4.2). The complete set of gait data corresponding to normal walking speed collected using Note-II device has been used for this experiment. Fig. 8 shows the scatter diagram of the top 3 features of the proposed HG feature vector. As expected, most of the data points belonging to male and female subjects are well separated in the three-dimensional feature space. Also, it is noteworthy that the distribution of these features belonging to male and female users is quite similar to the one shown in Fig. 7.

4.4. Effect of the number of gait cycles on the performance

To study the effect of the number of gait cycles on the performance of proposed approach, a set of experiments has been performed by varying the number of cycles employed for feature extraction. Fig. 9 shows the classification accuracy versus the number of gait cycles for datasets captured using S-II and Note-II (N-II) devices. As can be observed, the gender recognition accuracy increases with the number of gait cycles. These results indicate that employing more number of gait cycles for feature extraction leads to better characterization of the user's gender at the expense of the computational performance. Since the maximum number of gait cycles available for feature extraction is 7 for some of the users in the dataset, we have set this parameter to 7 in our experiments.

4.5. Comparison with the existing methods

The performance of the proposed approach has been compared with the existing approaches for gender classification (Jain & Kanhangad, 2016; Weiss & Lockhart, 2010). For a fair comparison, we

Table 6
Classification accuracy of the proposed and existing approaches for different walking speeds.

Reference	Classifier	Dataset					
		S-II			N-II		
		Normal	Fast	Slow	Normal	Fast	Slow
Weiss and Lockhart (2010)	NN	71.74%	79.76%	63.64%	73.77%	74.60%	75.16%
	IB3	72.83%	82.14%	60.23%	68.03%	73.81%	70.63%
	J48	82.61%	71.43%	54.55%	55.74%	68.25%	74.60%
Jain and Kanhangad (2016)		75%	67.50%	73.86%	74.75%	78.33%	65.79%
This work		**89.13%**	**92.22%**	**85.23%**	**88.52%**	**90%**	**84.21%**

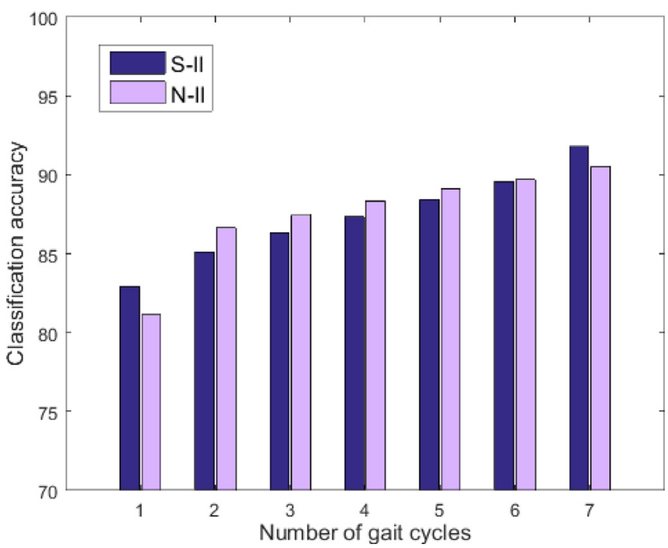

Fig. 9. Classification accuracy versus the number of gait cycles employed for gender recognition.

have implemented the approaches reported in Weiss and Lockhart (2010) and Jain and Kanhangad (2016), and evaluated their performances on our datasets. As has been done in Weiss and Lockhart (2010), the classification is performed using three classifiers namely, instance-based learning (IB3), J48 decision tree (J48) and multilayer neural network (NN), which are available in the Weka data mining tool (Hall et al., 2009). In this set of experiments, we have adopted the leave-one-out method (LOOM), which was used for performance evaluation in Weiss and Lockhart (2010). Results from this set of experiments, performed on the datasets collected using S-II and Note-II (N-II), are presented in Table 6. It can be observed from this table that the proposed approach achieves higher classification accuracy than the existing approaches. It is also noteworthy that our approach provides considerable performance improvement consistently for different walking speeds considered in this study.

The key strength of our approach is the discriminating power of the proposed HG features that provide superior performance. Apart from the information that these features carry, we believe that the way in which they are computed in our approach contributes to their higher discriminating power. Since the walking speed affects the duration of the gait cycles, we have extracted features from individual gait cycles. This approach makes the extracted features invariant to momentary changes in the user's walking speed. On the other hand, Weiss and Lockhart (2010) computed a set of statistical features using windows of fixed duration. Similarly, Jain and Kanhangad (2016) computed their local curvature-based features from segments of the gait signals that contain 8 cycles. Due to the fixed-length segments involved in their feature extraction process, the approaches mentioned above are likely to be adversely affected by momentary variations in user's walking speed. This is supported by our experimental results presented in Table 6. A disadvantage of the proposed approach is the higher dimensionality of our feature vector. In addition, our approach involves more parameters compared with the existing methods (Jain & Kanhangad, 2016; Weiss & Lockhart, 2010).

4.6. Summary of experimental results

This study considered more realistic conditions (compared to the existing studies) as we have carried out performance evaluation on two datasets collected using different devices. The experimental results suggest that the fusion of information extracted from linear acceleration and angular velocity gait signals leads to improved gender recognition. In addition, the results of our cross-speed experiments show that the proposed approach performs well when there is limited variation in the walking speed during the training and test sessions. In other words, the approach is likely to fail if this variation is significant. This is because HG features capture local gradient information by dividing the signal into a number of cells and the use of fixed-size cells in our approach resulted in intra-class variations in the extracted features. A straightforward way to overcome this problem is to adapt the cell size to the speed of walking. This can be achieved through coarse-grained classification of user's gait speed into categories such as slow, normal and fast and assigning appropriate cell sizes to each of these walking speeds.

5. Conclusion

In this paper, we have presented an approach for gender recognition in smartphones using gait biometrics. An android application is developed to acquire gait data using built-in accelerometer and gyroscope sensors of smartphones and a novel approach based on histogram of gradients is proposed for feature extraction. The key observations from our experiments can be summarized as follows:

(1) Features extracted from gyroscope sensor readings also carry information useful for gender classification in smartphones. More importantly, the feature-level combination of accelerometer and gyroscope sensor readings results in significant improvement of performance of the proposed approach.
(2) It is observed from the cross-speed experiments that variations in the user's walking speed have a minimal impact on the performance of proposed approach, except for cases where there is significant change in walking speeds between training and testing sets.
(3) Our experimental results also show that the performance of the proposed approach is consistent across two gait datasets collected using two different devices and it achieves higher classification accuracy than the existing works.

A limitation of the proposed approach, as indicated by our experimental results, is the drop in classification accuracy in scenarios where there is considerable change in subjects' walking speed between the training and testing sets. The classification accuracy of the proposed approach under such scenarios may not be sufficiently high for practical applications. A straightforward way to address this issue is to train the system with gait datasets covering an extensive range of walking speeds. However, a more efficient approach would be to extract features that are intrinsically invariant to variations in user's walking speed. Therefore, our future work will focus on this aspect of the gender classification in smartphones. In addition, we plan to explore advanced machine learning techniques to further improve the recognition accuracy.

The findings of our study lead us to the following research directions. Besides improving the performance, it is imperative to develop intelligent systems that perform gender recognition in more realistic and challenging scenarios that involve walking on level, inclined and uneven surfaces in indoor and outdoor environments (crowded place, rainy/sunny day, etc.). A scenario, in which users carry different objects while walking, may also be considered. One may also study gender recognition using gait data collected from the phone kept in different locations such as a pocket, handbag, and backpack. Additionally, we plan to develop a framework that utilizes the gender information for improving the performance of a biometric-based user authentication system in smartphones. Having achieved encouraging results for gender recognition, we will extend our work to identify other soft biometric traits (such as age, weight, height) and emotional states.

References

Agneessens, A., Bisio, I., Lavagetto, F., & Marchese, M. (2010). Design and implementation of smartphone applications for speaker count and gender recognition. *The internet of things: 20th Tyrrhenian workshop on digital communication*.

Albiol, A., Monzo, D., Martin, A., Sastre, J., & Albiol, A. (2008). Face recognition using HOG-EBGM. *Pattern Recognition Letters, 29*(10), 1537–1543.

Antal, M., & Nemes, G. (2016). Gender recognition from mobile biometric data. In *IEEE 11th international symposium on applied computational intelligence and informatics (SACI)* (pp. 243–248).

Arroyo, R., Yebes, J. J., Bergasa, L. M., Daza, I. G., & Almazán, J. (2015). Expert video-surveillance system for real-time detection of suspicious behaviors in shopping malls. *Expert Systems with Applications, 42*(21), 7991–8005.

Berkaya, S. K., Gunduz, H., Ozsen, O., Akinlar, C., & Gunal, S. (2016). On circular traffic sign detection and recognition. *Expert Systems with Applications, 48*, 67–75.

Bisio, I., Delfino, A., Lavagetto, F., Marchese, M., & Sciarrone, A. (2013). Gender-driven emotion recognition through speech signals for ambient intelligence applications. *IEEE Transactions on Emerging Topics in Computing, 1*(2), 244–257.

Breiman, L. (1996). Bagging predictors. *Springer Machine learning, 24*(2), 123–140.

Cao, L., Dikmen, M., Fu, Y., & Huang, T. S. (2008). Gender recognition from body. In *Proceedings of the 16th ACM international conference on multimedia (MM '08)* (pp. 725–728).

Chen, C., & Ross, A. (2011). Evaluation of gender classification methods on thermal and near-infrared face images. In *International joint conference on biometrics (IJCB)* (pp. 1–8).

Choi, Y., Kim, Y., Kim, S., Park, K., & Park, J. (2016). An on-device gender prediction method for mobile users using representative wordsets. *Expert Systems with Applications, 64*, 423–433.

Dalal, N., & Triggs, B. (2005). Histograms of oriented gradients for human detection. In *IEEE conference on computer vision and pattern recognition (CVPR)* (pp. 886–893).

Danisman, T., Bilasco, I. M., & Martinet, J. (2015). Boosting gender recognition performance with a fuzzy inference system. *Expert Systems with Applications, 42*(5), 2772–2784.

Duda, R., Hart, P., & Stork, D. (2001). *Pattern classification* (2nd ed.). John Wiley & Sons.

Gnanasivam, P., & Muttan, S. (2012). Gender classification using ear biometrics. In *Proceedings of the 4th International Conference on Signal and Image Processing (ICSIP)* (pp. 137–148).

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA data mining software: An update. *SIGKDD Explorations, 11*(1), 10–18.

Hu, M., Wang, Y., Zhang, Z., & Zhang, D. (2011). Gait-based gender classification using mixed conditional random field. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 41*(5), 1429–1439.

Igual, L., Lapedriza, A., & Borras, R. (2013). Robust gait-based gender classification using depth cameras. *EURASIP Journal on Image and Video Processing*.

Jain, A. K., Nandakumar, K., Lu, X., & Park, U. (2004). Integrating faces, fingerprints, and soft biometric traits for user recognition. *Biometric Authentication Lecture Notes in Computer Science, 3087*, 259–269.

Jain, A., Nandakumar, K., & Ross, A. (2005). Score normalization in multimodal biometric systems. *Pattern Recognition, 38*(12), 2270–2285.

Jain, A., & Kanhangad, V. (2016). Investigating gender recognition in smartphones using accelerometer and gyroscope sensor readings. In *IEEE international conference on computational techniques in information and communication technologies* (pp. 597–602).

Kastaniotis, D., Theodorakopoulos, I., Economou, G., & Fotopoulos, S. (2013). Gait-based gender recognition using pose information for real-time applications. *18th international conference on digital signal processing (DSP)*.

Li, X., Maybank, S. J., Yan, S., Tao, D., & Xu, D. (2008). Gait components and their application to gender recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, 38*(2), 145–155.

Li, X., Zhao, X., Fu, Y., & Liu, Y. (2010). Bimodal gender recognition from face and fingerprint. In *IEEE conference on computer vision and pattern recognition (CVPR)* (pp. 2590–2597).

Lu, X., Chen, H., & Jain, A. K. (2005). Multimodal facial gender and ethnicity identification. *Proceedings of Advances in Biometrics, 3832*, 554–561.

Lu, J., Wang, G., & Moulin, P. (2014). Human identity and gender recognition from gait sequences with arbitrary walking directions. *IEEE Transactions on Information Forensics and Security, 9*(1), 51–61.

Miguel-Hurtado, O., Stevenage, S. V., Bevan, C., & Guest, R. (2016). Predicting sex as a soft-biometrics from device interaction swipe gestures. *Pattern Recognition Letters, 79*, 44–51.

Minutolo, A., Esposito, M., & Pietro, G. (2015). Design and validation of a light-weight reasoning system to support remote health monitoring applications. *Engineering Applications of Artificial Intelligence, 41*, 232–248.

Ng, C. B., Tay, Y. H., & Goi, B. M. (2012). Vision-based human gender recognition: A survey. *Computer Vision and Pattern Recognition*. arXiv preprint. arXiv: 1204.1611.

Ogunduyile, O. O., Zuva, K., Randle, O. A., & Zuva, T. (2013). Ubiquitous healthcare monitoring system using integrated triaxial accelerometer, S_pO_2 and location sensors. *International Journal of UbiComp, 4*(2), 1–13.

Park, U., & Jain, A. K. (2010). Face matching and retrieval using soft biometrics. *IEEE Transactions on Information Forensics and Security, 5*(3), 406–415.

Ren, Y., Chen, Y., Chuah, M. C., & Yang, J. (2015). User verification leveraging gait recognition for smartphone-enabled mobile healthcare systems. *IEEE Transactions on Mobile Computing, 14*(9), 1961–1974.

Shan, C., Gong, S., & McOwan, P. W. (2008). Fusing gait and face cues for human gender recognition. *Neurocomputing, 71*(10-12), 1931–1938.

Su, B., Lu, S., Tian, S., Lim, J. H., & Tan, C. L. (2014). Character recognition in natural scenes using convolutional co-occurrence HOG. In *22nd IEEE international conference on pattern recognition* (pp. 2926–2931).

Thang, H. M., Viet, V. Q., Thuc, N. D., & Choi, D. (2012). Gait identification using accelerometer on mobile phone. In *International conference on control, automation and information sciences (ICCAIS)* (pp. 344–348).

Thomas, V., Chawla, N. V., Bowyer, K. W., & Flynn, P. J. (2007). Learning to predict gender from iris images. *IEEE international conference on biometrics: Theory, applications, and systems*.

Vergeest, L. (2013). *Uses, gratifications and gender in smartphone use*. Academia.edu. Tilburg University.

Wang, Y., Tang, Y., Ma, J., & Qin, Z. (2015). Gender prediction based on data streams of smartphone applications. In *International conference on big data computing and communications* (pp. 115–125).

Weiss, G. M., & Lockhart, J. W. (2010). Identifying user traits by mining smart phone accelerometer data. In *5th international workshop on knowledge discovery from sensor data* (pp. 61–69).

Wu, M., & Yuan, Y. (2014). Gender classification based on geometry features of palm image. *Hindawi Publishing Corporation, The Scientific World Journal, 2014*, 1–7.

Yu, S., Tan, T., Huang, K., Jia, K., & Wu, X. (2009). A study on gait-based gender classification. *IEEE Transactions on Image Processing, 18*(8), 1905–1910.

Zhang, D., & Wang, Y. (2009). Gender recognition based on fusion of face and multi-view gait. *Advances in Biometrics Lecture Notes in Computer Science, 5558*, 1010–1018.

Zhang, Y., Pan, G., Jia, K., Lu, M., Wang, Y., & Wu, Z. (2015). Accelerometer-Based Gait Recognition by Sparse Representation of Signature Points with Clusters. *IEEE Transactions on Cybernetics, 45*(9), 1864–1875.

Zhong, Y., & Deng, Y. (2014). Sensor orientation invariant mobile gait biometrics. In *IEEE international joint conference on biometrics (IJCB)* (pp. 1–8).