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A Brief Literature Review of some Efficient Human Gait Analysis Based Gender Classification Techniques

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Abstract: Gait based gender classification is an emerging area in the field of biometrics that has received a lot of interest from researchers mainly due to its advantages over the other methods and its potential application. Gait based gender classification helps a vision based biometric analysis system by focusing the gender-unique features. This helps to improves the performance of the model by limiting the authentication database searching to only one gender. Through the years, researchers have tried a wide variety of techniques and their combinations to improve the accuracy of gait based biometric systems in varying use-cases. In this study, we have given a brief overview of some of the recent and pioneering works done in the field of gait-based gender classification.

Index Terms: Gait, Biometrics, classification, gender, Gait cycle

1. Introduction

Every person in the world has physical features which are completely unique. These features can be used to determine a person's identity and are known as biometric traits. The study of analyzing these traits for recognition is called biometrics. In the recent years, with the increase in critical security issues like terrorism, a lot of focus has been put on biometric recognition. As a result, various biometric technologies have been developed to identify a person. These technologies analyze different features of a person like fingerprint, iris, palm prints, gait and sometimes a combination of two or more features [1,10,21].

One of the newer and emerging areas of development is gait biometrics. Due to its unobtrusive nature, it has been considered as an ideal candidate by many researchers for the new mainstream security and recognition system.

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Gait is defined as the way or the manner in which a person walks. It's not affected by a single part of body like arms, legs, hips, and shoulders, but rather it is a product of the relative movement of all of them. Almost all of the gait-based research approaches use videos as their dataset. This is because extracting required frames from the videos is easier and quicker than using images. It also allows to make use of temporal and spatial data which is not possible when working with images. However, most researchers prefer to only use spatial data [2,3,4,5,11,14,17,18,19,20,21,24].

The reason that gait biometrics is being touted as the emerging area in the area of biometric research is because of the advantages it holds over the existing biometric technologies:

- A person's gait is a behavioral trait, meaning that the components required to observe it are unobtrusive and can monitor gait from a distance. Other biometric technologies like facial recognition and fingerprint recognition require very close or physical contact to work.
- Unlike facial and iris biometrics which require the images to be of a good resolution and the subject to look directly at the camera, gait patterns can be obtained even from low quality images.
- A person's gait is affected by multiple body characteristics, such as muscle activity, skeletal structure, and the length of the limbs. All these traits combined makes gait a very complex behavioral trait which make it very difficult to copy a person's gait. This guarantees good security.
- Despite the introduction of other factors such as injury or change in body weight, gait biometrics can still provide some degree of recognition. In comparison, commonly used biometrics like fingerprint fail to recognize the subject if an injury to the body part being scanned is introduced.

Another emerging use of biometric technologies is to determine the gender of a person. Gender of a person is a trait that plays a major role in all social interactions. Gender recognition is a very useful asset in making intelligent security and surveillance systems. It has many potential uses in everyday life, such as monitoring gender specific customer traffic.

The Model-free approach for gait based classification, although being robust has a major shortcoming in the form of its accuracy being heavily dependent on the angle of the subject with respect to the imaging device. To address this problem, algorithms such as Support Vector Machines(SVM) and CNN have been used, but with limited success. While some approaches prove to be better than others, the overall accuracy when compared to model-based approach still lacks more research.

2. Methodology

Automatic gender recognition can be achieved by facial recognition, voice analysis and gait analysis. Gait based gender recognition has become an interesting choice for researchers as it can be detected at a distance, is non- contact and non-invasive as opposed to the other two techniques. There has been some astounding work in this area in the past [30] [31]. In some attempts for gait-based gender classification, motion trackers motion tracking equipment are fixed at the major joints of the subject's body, and they were made to walk while wearing swimsuits [8]. This approach was unrealistic as in real life use, the subjects can't be made to wear trackers.

Since the body structure of every person is different, the resultant gait also varies significantly. Saunders et. Al [27] in their research described human walking as "translation of center of mass of the body from one point to another in a way that requires the least energy". This phenomenon is also called locomotion. They took into consideration five main constituents of human's motion, i.e., pelvic tilt, pelvic rotation, knee and foot mechanisms, knee flexion and the motion of pelvis. Jeffrey E. boyd in 2005[28] described gait as a cyclic combination of coordinated movements.

The process of walking is comprised of two phases. Swing and stance. A complete cycle which starts with swinging phase and ends with stance is called one stride.

Gait Cycle: Gait cycle is calculated by counting the amount of foreground pixels in the silhouettes in each individual frame captured with the silhouette in it. This number at its maximum when distance between the two legs is greatest (full stride stance) and reaches its minimum when the legs overlap in the frame. Two consecutive strides make one gait cycle. [29].

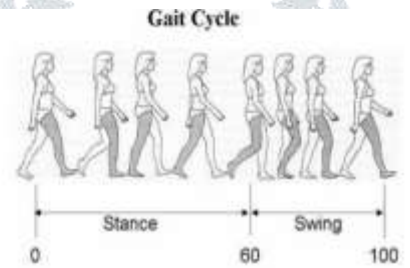

Figure. 1. Gait cycle [36]

Cycle Time: It is the ratio of gait period to the frame rate.
Speed: It is the rate of the forward motion of the body usually measured as meters per second.
Speed (m/sec) = Stride length (m) /cycle time (sec)
Stride Length: It can be determined by the coordinates of the forward displacements of the gait signatures during one gait cycle.
Gait-based classification is possible by two techniques:

- Model based approach: In this approach the system extracts features by identifying main joints of the body responsible for movement. It maps the joint from points like head to pelvis, pelvis to the two legs. Using this data, it essentially models the movement of the subject to classify their gender. This approach is more accurate but requires the images to be high resolution else the accuracy of the system starts suffering.
- Model free approach: In this system doesn't model the individual joints of the subject as features, but it considers the entire silhouette of the person as a feature. This allows it be fairly robust, and the system can work even with lower quality images. However, it is prone to accuracy problems due to view variation of the person.

3. Literature Survey

Tarun Choubisa et al [6] attempted to identify the gender of a person while using complete side view angle images. They also focused on the classification of gait direction of a dog and a human using Convolutional Neural Network (CNN). In addition, the various aspects of their system's CNN like the attention heat map, etc. can be visualized which gives some insight for the classification. It was found that in case of identification of females, the attention heatmap were continuous and concentrated. While in the case of identifying male subjects, the heatmaps were focused on lower region of legs, foot and wrists. Appropriate examples of heatmaps for both genders have been provided in Figures3 and Figure 4 respectively. The gender classification accuracy was found to be 93.3 % and the direction recognition accuracy was 94%.

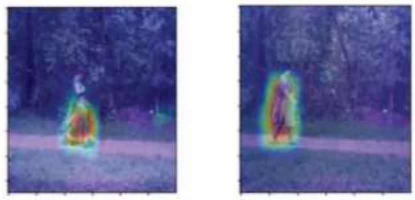

Figure. 2. Visualization of CNN heatmap for women[6]

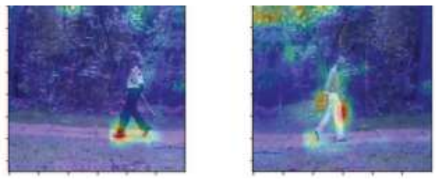

Figure. 3. Visualization of CNN heatmap for men.[6]

Mohammed Hussein Ahmed et al [12] presented his technique for gait-based gender classification based on the Kinect sensor. He also designed a model based on dynamic features called DDF(Dynamic Distance Feature). Kinect sensor was used as it could provide the skeletal view of subjects while tracking 20 joints of the body. The sensor then provides X-axis and Y-axis position of all joints. This gave the researchers 40 attributes for each subject which allowed them to create Dynamic Distance Features. An example of the DDF based model is shown in Fig. 4. Classifiers like LDC(Linear Discriminant Classifier), SVM(Support Vector Machine) and NN(Nearest Neighbor) were also used separately. The experiments were done with their own dataset therefore it is not possible to compare its accuracy with other researchers' approaches. It was observed that among the three classification techniques, KNN classifier achieved the highest classification accuracy. The gender classification accuracies achieved by SVM(Support Vector Machine), LDC(Linear Discriminant Classifier) and Nearest Neighbor (NN) were 90%, 91.1% and 96.7 % respectively.

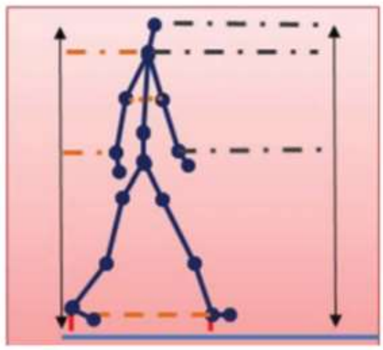

Figure. 4. Dynamic Distance Feature [12]

Mustafa Eren Yildirim1 et al [13] worked upon gender prediction problems encountered in working on a 3D space. In his research, horizontal, Vertical and depth-based coordinates of 20 distinct joints of walking subjects were acquired using Kinect sensor. In the next step absolute difference between mean values of class features for male and female was calculated. This means that for each subject 60 attributes were acquired. Work and benchmarking was done with genetic algorithm with taking samples from an open source dataset from UPCV. Gait was captured with help of Microsoft Kinect, which consisted of 5 gait samples from thirty people. The research made use of a multilayer Perceptron for training, and testing purposes. The approach achieved higher degree of performance with lesser computation times [13].

Lei Cai et al [14] in his research emphasized on the issue that gender classification in real life scenarios was challenging because many external factors such as view variations, arbitrary shapes of the pedestrians, etc. were also incorporated in the images. To address this, they developed a Multi-aspect Joint Learning Network or MJLN which reflects the influence of the pedestrian understanding to the identification of the pedestrian's gender. After receiving inputs, their system simultaneously performed gender learning and view learning. For the research pedestrian databases from multiple sources were used, namely VIPeR, CUHK, PRID, GRID and MIT. It was found that their proposed system was very effective and even performed better than some state-of-the-art systems. Table I provides a comparison of the performance of their system against other approaches in two metrics, i.e., Mean Accurate Predictions (MAP) and Area Under ROC Curve (ROC).

Table. 1. Comparing Performance of MJLN against other techniques

Methods	MAP	AUC	Reference
Mini-CNN	0.80	0.88	[46]
Alexnet-CNN	0.85	0.91	[46]
VGGNet16	0.87	0.89	[47]
GoogleNet	0.90	0.91	[48]
ResNet50	0.89	0.91	[49]
HDFL	0.94	0.95	[50]
MJLN	0.94	0.96	[14]

The work done by Sneha Choudhary et al [17] consists of four stages. Every silhouette image in a gait cycle for individual subjects are first normalized and then averaged. By making use of the principal component analysis, the size of resultant GEI image is also reduced. Five key spatial factors i.e., speed, gait, cadence, posture period length, height are then computed from the reduced GEI Image. In the final step the resultant parameters are concatenated to the GEI image. The attained feature vector set was trained and tested using the SVM (Support Vector Machine) and ANN (Artificial Neural Network). The Extreme accuracy that was attained was 98.16% which is slightly better than other approaches.

Jiwen Lu, et. Al in 2012 [39] investigated the issue with gait based gender determination in unconstrained environments. They calculated Average Gait Image (AGI) for individual groups and then trained the system to get a distance at which intra class variations are minimum and interclass variations are maximum. It was to make sure that more amount of information could be extracted which would improve accuracy. The table below compares jiwen lu's metric learning methods with other methods.

Table. 2. Comparing Performance against other techniques

Method	Correct Classification Rate
NCA [7]	88.8 %
LMNNN[41]	87.5 %
ITML [42]	86.3 %
Jiwen lu's approach [39]	91.3%

Maodi Hu et. al [43] made a novel attempt for gender classification which improves robustness of the system towards segmental noise and also provided a way to remove the external factors such as wearing clothing and carrying objects. They used CASIA gait database(B) for obtaining the samples. The table provided below compares the Correct Classification Rate (CCR) or the accuracy of their approach with other approaches.

Table. 3. Comparing Performance against other techniques

Method	Dataset	CCR
Lee et al. [44]	25 male, 25 female	85.0 %
Huang et al. [45]	25 male, 25 female	85.0 %
X. Li et al. [19]	31 male, 31 female	93.28 %
Shigi yu et al. [20]	31 male, 31 female	95.97 %
Maodi hu et al. [43]	31 male, 31 female	96.77 %

Zhang De[16] proposed an approach in which he attempted to classify the gender of a person by analyzing a multiple view fusion of the subject's gait. First, video inputs from four different viewpoints are used to create Gait Energy Images (GEI). The GEI and camera images are fused together to form a third order tensor of the form (x,y,view). Then all views are integrated by reducing the dimensionality of the tensor objects using Multi-linear Principal Component Analysis (MPCA). The research uses the CASIA gait database. The results demonstrated the effectiveness of MPCA based feature fusion achieved a Correct Classification Rate(CCR) of 98.1 %. The table 4 below shows the comparison of CCR of different viewing angles and the CCR of the fused result. Table 5 compares the CCR of the approach with other approaches.

Table. 4. CCR of gender recognition using SVM with linear kernel

Viewing Angle	Correct Classification Rate
0^0	72.3%
18^0	73.4%
36^0	76.4%
54^0	91.7%
72^0	93.0%
90^0	94.8%
108^0	92.1%
126^0	84.3%
144^0	78.1%
162^0	75.6%
180^0	74.2%
Fusion of all views	98.1%

Table. 5. Comparing performance against other approaches

Method	Number of Subjects	View angles	CCR
[44]	14 M & 10 F	90^0	84.5%
[45]	30 M and 30 F	$0^0,90^0,180^0$	89.5%
[19]	31 M and 31 F	90^0	93.2%
[20]	31 M and 31 F	90^0	95.9%
[16]	31 M and 31 F	$0^0,\ldots,180^0$	98.1%

Huang and Wang[45] proposed an approach for creating a robust gait-based gender classification system. Their research made use of Support Vector Machine(SVM) and Probabilistic Neural Network(PNN) while working on CASIA gait database (B). They extracted the features on the basis of anatomical division and binary moments. They considered 26 parameters in total and the irrelevant features were removed. Experimental results showed that their approach achieved 100% accuracy when compared to other research making use of same gait database. The below table shows the comparison of their research results.

Table. 6. Comparing performance against other approaches

Method	Dataset	CCR
Huang & Wang[45]	25 M & 25 F	85.5
Xuelong et. al. [19]	31 M & 31 F	93.28
Yu et al. [20]	31 M & 31 F	95.97
Maodi hu et al. [43]	31 M & 31 F	96.77
Maodi hu et al. [15]	31 M & 31 F	98.39
L.R sudha et al.[36]	31 M & 31 F	100

s

4. Conclusion and Future work

As seen in the literature survey, some algorithms and extraction techniques provide a better result than others. Using Gait Energy Image (GEI) for image extraction is an excellent alternative to other simpler methods. In the case of classification algorithms, Artificial neural networks and CNN produce much better results than algorithms like Support Vector Machine (SVM) and Linear Discriminant Classifier (LDC). Using this knowledge, systems using such algorithms can be designed to produce gait based classification systems which show excellent results despite variations in angle of subjects. Table 7 below provides a condensed comparison of the accuracies of the works discussed.

Table. 7. Collective Comparison of performance

Sr. No.	Reference	Database	Accuracy
1	Tarun Choubisa et al [6]	Self system Generated	93.3%
2	Mohammed Hussein Ahmed et al [12]	Microsoft kinect	NN – 96.67%, LDC – 91%, SVM – 90%
3	Mustafa Eren Yildirim1 et al [13]	UPCV	-
4	Lei Cai et al [14]	VIPeR, CUHK, PRID, GRID and MIT	94%
5	Sneha Choudhary et al [17]	CASIA B	98.16%
6	Jiwen Lu, et. Al in 2012 [39]	CASIA B	91.3%
7	Maodi Hu et. al [43]	CASIA B	96.77%
8	Zhang De[16]	CASIA	98.1%
9	L.R. Sudha and R. Bhavani [36]	CASIA B	100%

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