

Recognition of Gender using Gait Energy Image Projections Based on Random Forest Classifier

M. Hema, K Babulu, N Balaji

Abstract: Identification of gender is a very fascinating criterion in the present day scenario. Especially, in the surveillance applications, gender recognition is very beneficial. With the use of face, speech, voice and gait, the gender of a person can be determined. Non-contact, non-invasive and easily acquired at distance, gait analysis has attracted the interest of many researchers in the classification of gender. For the identification of gender, 2 stages of the methodology are used in our proposed work. A new descriptor called Gait energy image projection model(GPM) is proposed which highlights all the gender-related parameters. In the second stage of methodology, proposed descriptor GPM is fused with already existing descriptors like GEI and FED for enhanced performance. For classifying the gender, an Ensemble classifier called Random Forests is applied to the individual and fused descriptors and the results are evaluated. Two datasets are used for experimentation namely CASIA B and OU-ISIR datasets which are standard datasets for person identification and different performance metrics such as accuracy, precision, recall and error rate are evaluated.

Keyword: Image Recognition, Gait Energy Image, CASIA B dataset, Random Forest Classifier

I. INTRODUCTION

In the category of social communication, recognition of gender has an eminent role. Footprints, face, sound and gait are different biological features that can be applied for gender perception. When compared with face (or) voice[1], for the handling of long-distance perception, gait analysis is best suitable. Some unique characteristics are present in gait analysis like accessible collection, non-aggression and non-contact which placed gait analysis at the highest priority in identifying a person's gender in contrast to any other biometric techniques.

In current days, biometric technology is the fastest growing and emerging techniques in recognising a person. For the confirmation of a person, generally, there is a requirement of reliable person recognition schemes. The prominent role of such recognition schemes is to confirm that, the services are used only by the authorised users, not by any other individuals. Accessing of ATMs, laptops are very familiar examples for secure access.

Gait is an essential way of locomotion. Two significant categories are considered in the present-day gait scenario. Model dependent approaches and Silhouette dependent approaches are two different categories of gait.

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To obtain a series of static and dynamic categories of gait, model-based methods come into picture which establishes a mathematical model that represents dynamic changes in walking. To recognise the gender, silhouette based method utilises the silhouettes of gait sequence characteristics because of their low computational complexity and noise reduction[2]. There are many parameters and factors that affect the pattern of gait. They may be permanent factors (or) transient factors. Appearance approach and non-appearance approach are two approaches in gender classification. In the appearance approach, different features are considered are for gender identification like static features of a body such as facial expressions, eyebrows, hand shape etc, Dynamic features like the motion of a person, a gesture of a person, the gait of a person which is called walking style of a person[3]. In the apparel characteristics of a person, we consider hair style and clothing of a person, with the help of footwear of a person, the identification of an individual can be done with efficient accuracy. When non-appearance case of recognition, biological features comes into the picture. Based on the biological features of a person, biometric features of an individual are used like iris, voice and speech are analysed. Bio-signals like DNA of a person, ECG signals are highlighted for gender recognition. So, with the help of different features, the perception of gender can be performed in an efficient and abrupt manner[4].

Estimating human gender at a farther distance has several applications and also found solutions for face-based approaches disadvantages. Hence, in the present paper, the highlighted concepts are different features of gender on human gait which cited some great work dealing with gender classification based on gait at the beginning. For the underscore of the relevant gender gait features, we introduce the proposed descriptor. As the estimation of gender by gait is a tough job, the idea of fusion is introduced that can improve recognition performance. Many of the recent works in the fusion of information explained that the several features fusion achieves better performance and robustness. It overcomes the individual feature-based identification method in many applications. The experimentation also showed that the descriptors fusion had given splendid results when compared with the individual features recognition rate.

The current paper is presented as follows: firstly, the work that is related to our proposed work is represented in section 2. Next, the descriptor that is proposed for gender determination is given and the existing features that are used for respective work are described.

In section 4, the fusion of the proposed and the existing descriptors are presented. Later section of the paper discusses the performance of the different evaluation metrics such as accuracy, precision and recall of gender. And, at last, the conclusion of the proposed work and future scope is discussed.

II. RELATED WORK

Basically, humans have the capability of determining the gender of seeing a person. But, there are some cases, where the person is not clearly seen (or) observed through the human eyes. For example, in scrutinizing systems (or) in monitoring systems, a person is observed and captured through a camera. When the resolution of the captured image is low, then the person's details like gender (or) age can't be identified easily. To resolve this problem, we come across the gait analysis.

Gait has two modes of approaches for performing the analysis in recognizing a person's features. They are Model-independent and Model dependent approaches. In the Model-independent approach, the pre-defined model will be absent. There are no assumptions on the description of the model. Moving on to the model-dependent approaches, the assumptions are made on the past research work and modelling of the model is done based on the assumptions. Generally, model-independent approaches are highly preferable than model-dependent approaches.

In the past days, by using the facial features such as the shape of the individual's face, its geometry and its appearance, the gender can be determined. In one of the research work, based on face based features, gender is determined. Gender and age estimation can be done by observing the eyebrows, the way of clothing, the hair style and body shape. Static body features[5] and Dynamic body feature are the most appropriate features for the determination of the gender of a person. Many research works are done[6] based on these features and gained good accuracy in gender recognition[7].

In the case of age prediction, the images of the faces that are taken at low resolution are not that suitable and analysis of such images is also not possible. Hence, the approaches using gait came into existence for determining the gender of a person as it is best suited for analysing low-resolution images. As gait is referred to as the human walking, many of the gender-related parameters like stride length, cadence speed will be different for different persons.

There are some research works done by researchers in the literature. For the calculation of contour-based information for the extraction of gait features,[8] showed age classification by using the descriptors such as FED, HMM[9] which gave some improvement in the recognition. Work is done in the gender classification for the finding of gait differences. For the extraction of gait features, the silhouette is used and it is described in the frequency domain. Depending on this work, many parameters in connection to gait are clearly demonstrated which differentiate the younger and elder.

The research work is also done based on the apparel features of a person for gender prediction by using footwear and clothing conditions and obtain better outcomes. There are some other features for this work such as Gait energy image which is generally used in gender perception and

gave splendid results in its performance. Many research works are done based on GEI which is obtained from silhouettes to extract the spatial information and temporal information. But, there are some failures in using the GEI, that is, there is some unwanted information which occupies more amount of storage space.

Some of the authors suggested a new approach using the Gabor filters for the feature extraction which is suited for orienting the body shapes of the silhouettes. Many research works are performed based on the silhouettes, which is the important tool required for extracting any feature based on the applications.

In the gait analysis, determining gender is a complicated task. To overcome this problem, the concept of fusion is introduced. With the fusion of different gait features, the accuracy is enhanced and the performance of the descriptors will also be increased. So, the concept of fusion is introduced for the proposed and existing descriptors.

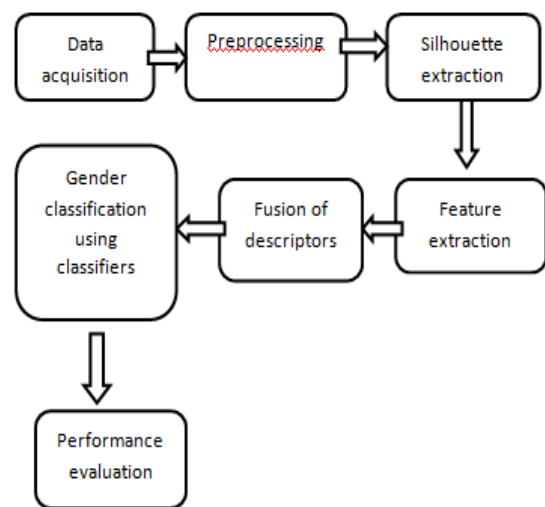


Fig. 1 Gender taxonomy

Research works are done on biological features for identifying the gender of a person. By analysing the biological features such as speech given by a person, based on fingerprints, based on the voice, the determination of a person is done. But, the biological features are noise sensitive and the information may be corrupted. As a result, the results produced from this noisy information may not be correct. So, gait analysis is considered as the best suitable solution for gender prediction[10].

III. PROPOSED METHOD

A. Overview of the method

In the framework of determining the gender of a person, some sequence of steps is to be implemented to extract the person's related features for gender.

B. Proposed Methodology

In the proposed work, two stages have to be implemented to classify the gender. In the first step, the Gait Energy Image Projection Model (GPM) is introduced which presents the vital gender-related parameters such as body size, head pitch, arm swing and stride length variations that characterise the gender in the respective gait cycle shown in Fig 2.



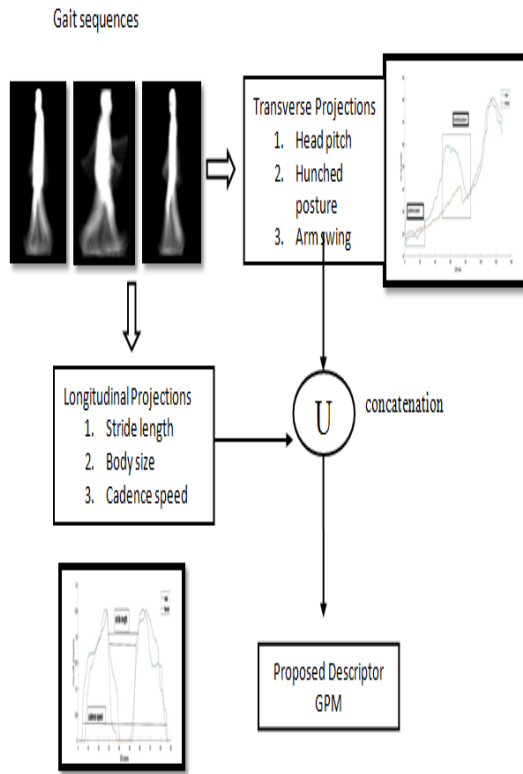


Fig. 2 Proposed Descriptor

Two projections are present in GPM. They are Gait Energy Image longitudinal projection (GLP) and Gait Energy Image transverse projection (GTP). The GLP explains the stride length and body size whereas the GTP gives the details regarding the head pitch, hunched posture and arm swing of the GEI image sequences given in Fig. 3.

In this paper, by using GLP and GTP, a new method is proposed and in parallel, we are highlighting the gender-related gait features. GPM combines both GLP and GTP by the use of the concatenation technique

$$GPM = \{ GLP_{cycle} \cup GTP_{cycle} \} \quad (1)$$

Mathematically, GLP_{cycle} is defined as equation(2)

$$GLP_{cycle} = \frac{1}{M} \sum_{i=1}^M GLP_i \quad (2)$$

Here, M defines a number of frames; GLP_i defines the i th frame vector of GLP.

And GTP_{cycle} is defined as equation(3)

$$GTP_{cycle} = \frac{1}{M} \sum_{i=1}^M GTP_i \quad (3)$$

M defines a number of frames; GTP_i defines the i th frame vector of GLP.

Gait energy images (GEI): GEI represents the spatiotemporal information of silhouette images from the entire gait cycle. Averaging the silhouette from the entire gait cycle gives an energy image.

The $D(x,y)$ represents GEI and calculated by using equation (4)

$$D(x, y) = \frac{1}{N} \sum_{t=1}^N B_t(x, y) \quad (4)$$

Where N defines a number of gait cycle images; x and y are the coordinates of every image B .

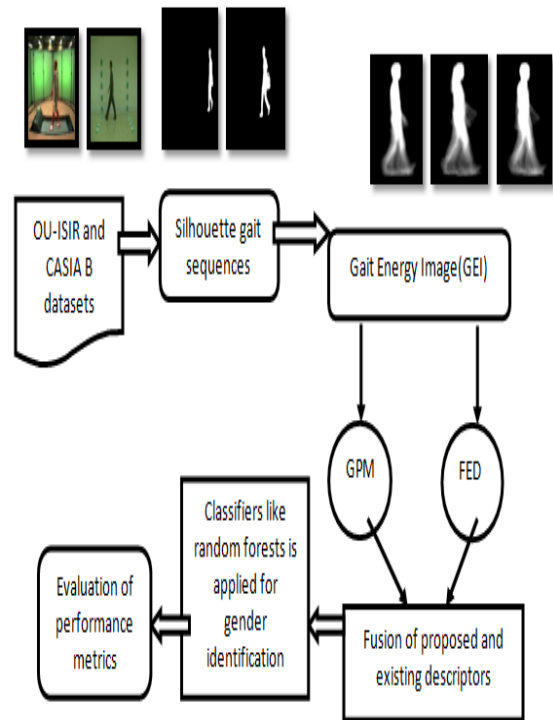


Fig.3 Flow chart of the proposed methodology

IV. DESCRIPTORS FUSION

Automatic gender estimation is a very critical task. To address this problem, the fusion of the proposed and existing descriptors is introduced. Many advances in the recent days showed that the fusion of multiple descriptors gives best results when compared to that of individual descriptor's performance.

There are different parameters that are used for gender estimation may overlap in nature. One parameter is linked with the other parameter. So, to obtain the results in an accurate manner, fusion is very useful.

In our proposed work, the individual descriptors GPM, GEI and FED are computed for all the image frames and the performance metrics are calculated for individual descriptors. Later, the individual descriptors are fused together to form a single descriptor, GGF: GPM, GEI and FED to obtain the information regarding all gender parameters and it is given as follows:

$$GGF = \{ GPM \cup GEI \cup FED \} \quad (8)$$

Then, the features, both individual and fused are computed for the datasets that are considered for experimentation and given to the classifier for the classification of gender.

V. EXPERIMENTS AND ANALYSIS

A. Datasets used

The experiments are conducted on two popular datasets namely OULP[11] dataset and CASIA B dataset which are generally used for age and gender estimation in many research work. CASIA B dataset is a multiview large database with 124 subjects. From 11 views, the data related to gait



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was captured. There are three(3) types of variations in CASIA B dataset namely carrying condition, clothing condition and view angle which are taken separately.

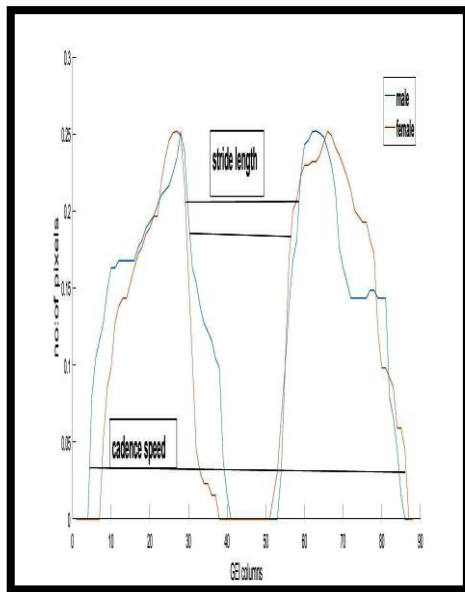


Fig. 4 GLP representation for male and female

OULP dataset is the frequently used dataset for gait analysis. It is a largely populated gait dataset which has 4007 persons. In that, 2135 persons are men and 1872 persons are women. When compared to another database, this OULP dataset is 20 times larger and has many advantages in using this dataset. Because the gender balance of males and females is good and variation of ages is also good when compared to other datasets.

B. Protocols considered for experimentation

The performance is evaluated for the individual descriptors as well as for the fused descriptors by taking the two datasets as the raw data. The experiment is done for five cross-validations where a different number of subjects are selected for different validations. The datasets are divided into training and testing set where 60% of the dataset is selected for training and 40% is selected for testing.

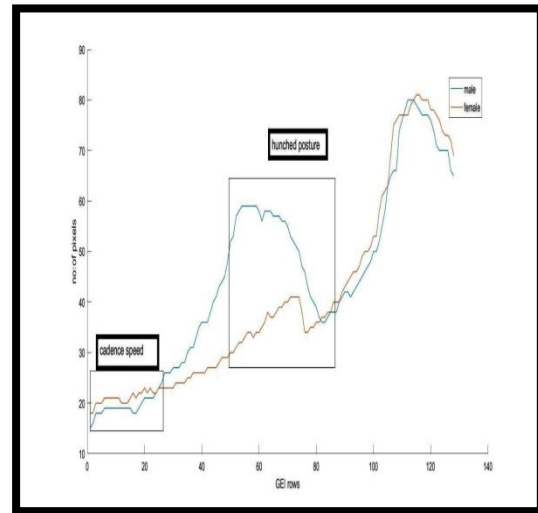


Fig 5. GTP representation of male and female

Performance evaluation is performed for all the validations and later, for the classification purpose, Random forests are used as gender classifications are binary cases. There are only two possible outcomes in age classification and gender estimation. Random forests are the best classifier in the case of ensemble learning[12]. With the help different classifiers, with the combination of different outputs which are produced in an independent manner, the ensemble learners are formed. As they are a combination of different weak learners, ensemble learners are best suitable and powerful learners in machine learning. The datasets considered for experimentation are unbalanced in the case of a number of persons. So, first the elder persons are selected and later the same number of young persons are selected for experiments. This case is also done in the case of gender classification.

C. Results

For the estimation of gender, the proposed descriptor and the existing descriptors are evaluated after applying the Random forests classifier by the performance metrics such as CCR, recall and precision. To explain the performance of any systems, these performance metrics are the best-suited ones. So, the performance metrics such as recall, precision and CCR are calculated for the individual descriptors as well performance is evaluated in terms of their of the performance metrics such as CCR, recall and precision.

Table 1: Results of descriptors of CASIA B dataset for gender estimation using Random forests

Descriptors	Recall _{elder} (%)	Recall _{younger} (%)	Precision _{elder} (%)	Precision _{younger} (%)	CCR(%)
GPM	75.00	88.88	63.63	99.21	86.12
GEI	66.76	80.95	63.63	89.12	76.76
FED	98.71	68.42	44.45	98.96	75.00
Fusion	90.90	92.30	90.90	92.30	91.66

Table 2: Results of descriptors of OULP dataset for Gender estimation using Random forests

Descriptors	Recall _{elder} (%)	Recall _{younger} (%)	Precision _{elder} (%)	Precision _{younger} (%)	CCR(%)
GPM	99.10	81.25	72.72	99.13	87.53
GEI	91.66	83.33	78.75	93.75	86.66
FED	84.21	99.89	81.81	94.73	83.33
Fusion	91.66	98.75	99.89	92.30	95.83

Table 1 explains the analysis of the results of CASIA B dataset in the estimation of gender recognition by using different performance metrics. The highlighted results are metrics that are obtained by performing five cross-validations which are calculated by fusion of the existing features with that of the proposed descriptor.

Table 2 gives the tabulated analysis of OULP dataset in gender estimation in terms of the performance metrics. The fusion of the proposed descriptor and the individual descriptor is also tabulated.

D. Analysis

It is observed from the results that are tabulated in Table 1, 2, that, the proposed descriptor GPM gives best results when compared with that of existing descriptors GEI and FED. GPM is the combination of two types of projections namely longitudinal and transverse projections. With the use of these projections, the changes that take place in the gait-related parameters, especially gender-related parameters are found clearly.

It is seen from Table 2 that, the results that are obtained for gender estimation has slight variations in using the OULP dataset. Because OULP dataset is the best-suited dataset for gender estimation due to its great balance in persons. GPM gives best results when compared to other existing descriptors. The fusion of the descriptors enhanced recognition results.

From Table 1, the CASIA B dataset is used for performance evaluation. Performance metrics are calculated for fused and individual descriptors for gender identification. It is clearly seen that GPM gave best results to that of existing descriptors. The fusion of descriptors[13] gave the best outcomes when compared to that of the individual descriptors. OULP dataset produced an excellent recognition rate in the case of gender. The reason behind these results is that OULP is the very large dataset with many persons which has great gender difference and age variations. CASIA B dataset has very minimum gender variations when compared to that of OULP dataset. So, identifying gender using CASIA B dataset is a very critical task. By using CASIA dataset, bag, cloth and view angle variations can be distinguished and found easily but gender-related parameters can't be found accurately[14]. This is the reason behind the OULP dataset to obtain the best recognition rate to that of CASIA dataset.

From the results obtained, it can be justified that, FED gave very low accuracy when compared to GEI and GPM because, while rotating the images in a counterclockwise direction by 6° , some of the parameters related to gender may be lost. So, the recognition rate will be decreased[15]. GEI is produced by averaging the images. In GEI, static information is not identified, which is important information to identify gender. GEI is insensitive to covariant changes. So, the results obtained using GEI is not that accurate[16]. GPM, which is our proposed descriptor, highlights all the gender parameters and is very sensitive to all the changes in the images. Hence, it gave the best results than GEI and FED. Fusion enhanced the results of recognition as it is a combination of many images[17].

For the classification of gender, an ensemble classifier called Random forests is used in the proposed work. Random forests are a combination of decision trees. With the help of different decision trees, different independent outputs are produced where independent errors are formed. In the selection phase, randomization is used for in decision

tree algorithm for attributes. When compared with the other machine learning algorithms, random forests gives better results in classification. Our proposed work also proved that random forests produce the best results in the classification of gender in gait analysis.

VI. CONCLUSION AND FUTURE SCOPE

In our proposed work, for classifying of the gender, different gender parameters in gait analysis are highlighted. For identifying the gender, GPM, which is the newly proposed descriptor, is presented. Transverse projections and longitudinal projections of the Gait energy images are explained in a detailed manner where the most important gender-related parameters are clearly highlighted.

For the enhancement of accuracy in the classification of gender, fusion is introduced in our proposed work. It is proved that a fusion of features increased the classification rate in identifying gender. In the future, the proposed work will be extended to the other classifiers and comparative analysis will be produced. For the identification of cross-gender, the proposed work will be extended. Finally, it is proved that gait analysis is best suitable for the person identification, in the perception of gender, especially in case of surveillance applications.

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