Recognizing Human Gender in Computer Vision: A Survey

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Abstract. Gender is an important demographic attribute of people. This paper provides a survey of human gender recognition in computer vision. A review of approaches exploiting information from face and whole body (either from a still image or gait sequence) is presented. We highlight the challenges faced and survey the representative methods of these approaches. Based on the results, good performance have been achieved for datasets captured under controlled environments, but there is still much work that can be done to improve the robustness of gender recognition under real-life environments.

Keywords: Gender recognition, gender classification, sex identification, survey, face, gait, body.

1 Introduction

Identifying demographic attributes of humans such as age, gender and ethnicity using computer vision has been given increased attention in recent years. Such attributes can play an important role in many applications such as human-computer interaction, surveillance, content-based indexing and searching, biometrics, demographic studies and targeted advertising. For example, in face recognition systems, the time for searching the face database can be reduced and separate face recognizers can be trained for each gender to improve accuracy [1]. It can be used for automating tedious tasks such as photograph annotation or customer statistics collection.

While a human can easily differentiate between genders, it is a challenging task for computer vision. In this paper, we survey the methods of human gender recognition in images and videos. We focus our attention on easily observable characteristics of a human which would not require the subject's cooperation or physical contact. Most researchers have relied on facial analysis, while some work have been reported on using the whole body, either from a still image or using gait sequences. We concentrate on approaches using 2-D (rather than the more costly 3-D) data in the form of still image or videos. Audio cues such as voice are not included.

In general, a pattern recognition problem such as gender recognition, when tackled with a supervised learning technique, can be broken down into several steps which are object detection, preprocessing, feature extraction and classification. In detection, the human subject or face region is detected and cropped from the image. This is

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followed by some preprocessing, for example geometric alignment, histogram equalization or resizing. In feature extraction, representative descriptors of the image are found, after which selection of the most discriminative features may be made or dimension reduction is applied. As this step is perhaps the most important to achieve high recognition accuracy, we will provide a more detailed review in later sections.

Lastly, the classifier is trained and validated using a dataset. As the subject is to be classified as either male or female, a binary classifier is used, for example, support vector machine (SVM), Adaboost, neural networks and Bayesian classifier.

The rest of this paper is organized as follows: Section 2, 3, and 4 review aspects (challenges, feature extraction, and performance) of gender recognition by face, gait and body, respectively, followed by concluding remarks in Section 5.

2 Gender Recognition by Face

The face region, which may include external features such as the hair and neck region, is used to make gender identification. The image of a person's face exhibits many variations which may affect the ability of a computer vision system to recognize the gender, which can be categorized as being caused by the image capture process or the human. Factors due to the former are the head pose or camera view [2], lighting and image quality. Head pose refers to the head orientation relative to the view of the image capturing device, as described by the pitch, roll and yaw angles. Human factors are age [3][4], ethnicity [5], facial expression [6] and accessories worn (e.g hat).

2.1 Facial Feature Extraction

We broadly categorize feature extraction methods for face gender classification into *geometric-based* and *appearance-based* methods [3][7]. The former is based on distance measurements of *fiducial points*, which are important points that mark features of the face, such as the nose, mouth, and eyes. Psychophysical studies using human subjects established the importance of these distances in discriminating gender. While the geometric relationships are maintained, other useful information may be discarded [3] and the points need to be accurately extracted [8]. Brunelli and Poggio [9] used 18 point-to-point distances to train a hyper basis function network classifier. Fellous [10] selected 40 manually extracted points to calculate 22 normalized fiducial distances.

Appearance-based methods are based on some operation or transformation performed on the image pixels, which can be done globally (holistic) or locally (patches). The geometric relationships are naturally maintained [3], which is advantageous when gender discriminative features are not exactly known. But they are sensitive to variations in appearance (view, illumination, etc.) [3] and the large number of features [8].

Pixel intensity values can be directly input to train a classifier such as neural network or support vector machine (SVM). Moghaddam and Yang [11] found that Gaussian RBF kernel gave the best performance for SVM. Baluja and Rowley [12] proposed a fast method that matched the accuracy of SVM using simple pixel comparison operations to find features for weak classifiers which were combined using AdaBoost.

Viola and Jones[13] introduced *rectangle or Haar-like features* for rapid face detection, and used for real-time gender and ethnicity classification of videos in [14].

Dimension reduction methods such as Principal Component Analysis (PCA), used in early studies [15][16], obtain an image representation in reduced dimension space, which would otherwise be proportionate to the image size. Sun et al. [17] used genetic algorithm to remove eigenvectors that did not seem to encode gender information. Other methods such as 2-D PCA, Independent Component Analysis (ICA) and Curvilinear Component Analysis (CCA) have also been studied [6] [18][19].

Ojala et al. [20] introduced *local binary patterns* (LBP) for grayscale and rotation invariant texture classification. Each pixel in an image is labeled by applying the LBP operator, which thresholds the pixel's local neighborhood at its grayscale value into a binary pattern. LBP detect microstructures such as edge, corners and spot. LBP has been used for multi-view gender classification [2], and combined with intensity and shape feature[21], or with contrast information [22]. Shan [23] used Adaboost to learn discriminative LBP histogram bins. Other variants inspired by LBP have been used for gender recognition, such as Local Gabor Binary Mapping Pattern [24][25][26], centralized Gabor gradient binary pattern [27], and Interlaced Derivative Pattern [28].

Scale Invariant Feature Transform (SIFT) features are invariant to image scaling, translation and rotation, and partially invariant to illumination changes and affine projection [29]. Using these descriptors, objects can be reliably recognized even from different views or under occlusion and eliminates the need for preprocessing, including accurate face alignment [30]. Demirkus et al. [31] exploited these characteristics, using a Markovian model to classify face gender in unconstrained videos.

Research in neurophysiology has shown that *Gabor filters* fit the spatial response profile of certain neurons in the visual cortex of the mammalian brain. Gabor wavelets were used to label the nodes of an elastic graph representing the face [32] or extracted for each image pixel and then selected using Adaboost [33]. Wang et al. extracted SIFT descriptors at regular image grid points and combined it with Gabor features [34]. Gabor filters have also been used to obtain the simple cell units in *biologically inspired features* (BIF) model. This model contains simple (S) and complex (C) cell units arranged in hierarchical layers of S1, C1, S2 and C2. For face gender recognition, the C2 and S2 layers were found to degrade performance [4].

Other facial representations that have been used include a generic patch-based representation [35], regression function [36], DCT [37], and wavelets of Radon transform [38]. Features external to the face region such as hair, neck region [39] and clothes [7] are also cues used by humans to identify gender. Social context information based on position of a person's face in a group of people was used in [40].

2.2 Evaluation and Results

A list of representative works on face gender recognition is compiled in Table 1. Because of the different datasets and parameters used for evaluation, a straight comparison is difficult. The datasets that have been used tend to be from face recognition or detection since no public datasets have been designed specifically for gender recognition evaluation. Evaluation metric is based on the accuracy or classification rate.

Table 1. Face gender recognition results

First Author, Year	**Feature extraction**	**Classifier**	**Training data***	**Test data***	**Ave. Acc.%**	**Dataset variety[@]**
Moghaddam, 2002 [11]	Pixel values	SVM-RBF	FERET 1044m 711f	5-CV	96.62	F
Shakhnarovich, 2002 [14]	Haar-like	Adaboost	Web images	5-CV Video seqs.	79 90	P (<30°), A,E,L
Buchala, 2005 [41]	PCA	SVM -RBF	Various mixes 200m 200f	5-CV	92.25	F
Jain, 2005 [18]	ICA	SVM	FERET 100m 100f	FERET 150m 150f	95.67	F,S
Baluja, 2006 [12]	Pixel comp.	Adaboost	FERET 1495m 914f	5-CV	94.3	F,S
Lapedriza, 2006 [42]	BIF multi scale filt.	Jointboost	FRGC 3440t FRGC 1886t	10-CV 10-CV	96.77 91.72	uniform background cluttered background
Lian, 2006 [2]	LBP histo-gram	SVM-polynomial	CAS-PEAL 1800m 1800f	CAS-PEAL 10784t	94.08	P (up to 30° yaw & pitch)
Leng, 2008 [33]	Gabor	Fuzzy SVM	FERET 160m 140f	5-CV	98	
Xu, 2008 [43]	Haar-like, fiducial	SVM-RBF	Various mixes 500m 500f	5-CV	92.38	F,E,A,L,S
Xia, 2008 [24]	LGBMP hist.	SVM-RBF	CAS-PEAL 1800m 1800f	CAS-PEAL 10784t	94.96	P (up to 30° yaw & pitch)
Aghajanian, 2009 [35]	Patch-based	Bayesian	Web images 16km 16kf	Web images 500m 500f	89	U
Li, 2009 [37]	DCT	SGMM	YGA 6096t	YGA 1524t	92.5	F,A,S
Lu, 2009 [6]	2D PCA	SVM-RBF	CAS PEAL 300m 300f	CAS-PEAL 1800t	95.33	F,X
Demirkus, 2010 [31]	SIFT	Bayesian	FERET 1780m 1780f	Video seqs. 15m 15f	90	U (P,X,O,L)
Wang, 2010 [34]	SIFT, Gabor	Adaboost	Various mixes 4659t	10-CV	~97	F,X,L,O
Lee, 2010 [36]	regression	SVM	FERET 1158m, 615f		98.8	F
Alexandre, 2010 [21]	Intensity, edge, LBP	SVM-linear	FERET 152m 152f UND set B 130m 130f	FERET 60m 47f UND set B 171m 56f	99.07 91.19	F,S F,S
Li, 2011 [7]	LBP, hair, clothing	SVM	FERET 227m 227f	FERET 114m 114f	95.8	F
Wu, 2011 [25]	LGBP	SVM-RBF	CAS-PEAL 2142m 2142f	CAS-PEAL 2023m 996f	~91-97 per set	P (up to 67° yaw), S
Zheng, 2011 [26]	LGBP-LDA	SVMAC	CAS-PEAL 2706m 2706f (of 9 sets) FERET 282m 282f	CAS-PEAL 2175m 1164f FERET 307m 121f	≥ 99.8 per set 99.1	P (up to 30° yaw & pitch), S F
Shan, 2012 [23]	LBP hist. bins	SVM-RBF	LFW 4500m 2943f	5-CV	94.81	F,U,S

*The number of male and female faces is given; e.g. 500m 500f refers to 500 male and female faces each. Where the number was not given, the total faces used are given (e.g. 1000t.)
When the accuracy is reported based on cross-validation result, this is indicated in the *test data* field; e.g. 5-CV refers to five-fold cross validation, and the average rate from validation results is given. If classification rate for a different test set is given, this result is used and the dataset is indicated.
[@] The variations controlled or the variety used,, as mentioned by the authors, are indicated as follows:
F–frontal only A–age E–ethnicity P–pose/view L–lighting X–expression O–occlusion
U – uncontrolled S – indicates the same individual does not appear on both training and test set

It is noted that the FERET dataset is the most often used (although the subset of images taken varies.) The best accuracy is 99.1%, using frontal face only [26][21]. Zheng et al. [26] achieved near 100% for pose variations up to 30° yaw and pitch on the CAS-PEAL dataset, with separate classifiers trained for each pose (thus requiring prior pose detection). For images taken in uncontrolled environments, Shan [23] obtained 94.8% on the LFW dataset containing frontal and near frontal faces.

3 Gender Recognition by Gait

Gait is defined to be the coordinated, cyclic combination of movements that result in human locomotion [44], which includes walking, running, jogging and climbing stairs. In computer vision research, the gait of a walking person is often used. Exploiting gait information is helpful in some situations such as when the face is not visible. In a video sequence of a person walking, the gait cycle can be referred to as the time interval between two consecutive left/right mid-stances [45]. Many factors affect the gait of a person, such as load [46], footwear, walking surface, injury, mood, age [47] and change with time. Video-based analysis of gait would also need to contend with clothing, camera view [47][48][49][50][51], walking speed and background clutter.

3.1 Feature Extraction

Early work on gait analysis used point lights attached to the body's joints. Based on the motion of the point lights during walking, identity and gender of a person could be identified [52] (see [53] for a survey on these early works). Human gait representation can be divided into *model-based* or *appearance-based* (*model-free*)[54][55]. Yoo et al., guided by anatomical knowledge, obtained 2-D *stick figures* from the body contour [56], of which a sequence from one gait cycle composed a gait signature. Such model-based approaches rely on accurate estimation of joints [55][57] and require high-quality gait sequences [45] where the body parts need to be tracked in each frame, thus incurring higher computational costs. Moreover, they ignore body width information [57]. However, they are view and scale invariant [45].

In many appearance-based methods, the *silhouette* of the human is obtained, for example using background subtraction. Lee and Grimson [58] divided each silhouette into 7 regions and fitted *ellipses* into each region. The mean and standard deviation of the ellipse moments together with the silhouette centroid height formed the gait features, with robustness to silhouette noise. However, it will be affected by viewpoint, clothing and gait changes [58]. Felez et al. [59] improvised by using a different regionalization of 8 parts to obtain more realistic ellipses while Hu et al. [57] used equal partitions formed by grids. Zhang and Wang [60] used *frieze patterns* to study multi-view gender classification. A *frieze* pattern is a two-dimensional pattern that repeats along one dimension. The gait representation is generated by projecting the silhouette along its columns and rows, then stacking these 1-D projections over time [61]. Shan et al. [62] showed that the *Gait Energy Image* (GEI) [63] was an effective representation for gender recognition by fusing gait and face features. A GEI represents human motion in a single image while preserving temporal information by averaging the silhouette images in one or more gait cycles, thus saving on storage and computational cost and is robust to silhouette noise in individual frames [63]. A similar representation, *Average Gait Image* (AGI) [64], averages over one gait cycle.

The GEI can also be estimated from a whole gait sequence, without the need to detect the gait cycle frequency [49]. Yu et al. [55] divided the GEI into 5 different components, with each given a weight based on the results from psychophysical experiments. Li et al. [65] partitioned the AGI into 7 components corresponding to body parts, while Chen et al. [50] used 8 components based on consideration of walking patterns. Lu and Tan [48] obtained the difference GEI from different views, using uncorrelated discriminant simplex analysis (USDA) for efficient projection into lower dimensional subspace.

Chen et al. [66] applied Radon transform on the human silhouettes in a gait cycle and used Relevant Component Analysis (RCA) for feature transformation. Oskuie and Faez [67] extracted Zernike moments from Radon-transformed Mean Gait Energy Image [68]. Frequency-domain features obtained from the silhouette using Discrete Fourier Transform (DFT) [47] and wavelet decomposition on the silhouette contour width [69] have been used. Instead of extracting the silhouette, DCT coefficients was obtained from the image to train embedded hidden Markov models [70]. Hu et al. [46] applied Gabor filters and used Maximization of Mutual Information (MMI) to learn the discriminative low dimensional representation.

3.2 Evaluation and Results

Table 2 shows representative works on gait-based gender recognition. For the CASIA Gait Database (Set B), state of the art performance is 98.39% using side view sequences only [57]. Slightly higher rate of 98.5% was reported by [67] using a gender imbalanced set. For real-time videos, 84.38% was achieved on a small set of four subjects [49]. 94% average accuracy was obtained for multiview sequences without requiring prior knowledge of the view angle [70]. For the IRIP Gait Database, Hu et al. [57] reported 98.33% using side view sequences. Chen et al. [50] achieved 93.3% by fusion of multiviews, requiring a camera per view, thus increasing complexity.

As a conclusion, gait-based gender recognition can achieve high classification rate in controlled datasets, especially with a single side view. There is a need for more investigation into generalization ability through cross database testing and performance for datasets with larger number of subjects in unconstrained environments.

Table 2. Gait-based gender recognition

First Author, Year	**Feature Extraction**	**Classifier**	**Training data**	**Test data**	**Ave. Acc.%**	**Dataset variety** [@]
Yoo, 2005 [56]	2D stick figures	SVM-polynomial	SOTON 84m 16f	10-CV	96%	N
Chen, 2009 [66]	Radon transform of silhouette	Mahalanobis distance	IRIP 32m 28f (300)	LOO-CV	95.7	N
Chen, 2009 [50]	AGI	Euclidean distance	IRIP 32m 28f (300 per angle)	LOO-CV	93.3	M(0°-180)
Yu, 2009 [55]	GEI	SVM	CASIA B 31m 31f (372)	31-CV	95.97	N
Chang, 2009 [49]	GEI+ PCA+LDA	Fisher boost	CASIA B 93m 31f (8856)	124-CV Videos	96.79 84.38	M(0°-180°) M(U)
Chang, 2010 [70]	DCT	EHMM	CASIA B 25m 25f	5-CV	94	M(0°-180°)

Table 2. (*Continued*)

Lu, 2010 [48]	GEI + UDSA	Nearest neighbour	CASIA B 31m 31f (4092)	LOO-CV	83-93 (per view)	M(0°-180°)
Felez, 2010 [59]	Ellipse fittings	SVM-linear	CASIA B 93m 31f (744)	10-CV	94.7	N
Hu, 2010 [46]	Gabor + MMI	GMM-HMM	CASIA B 31m 31f (372)	31-CV	96.77	N
Hu, 2011 [57]	ellipse fittings & stance indexes	MRCF	CASIA B 31m 31f (372) IRIP 32m 28f (300)	31-CV LOO-CV	98.39 98.33	N N
Handri, 2011 [69]	silhoutte contour width	kNN	Private 29m 14f (>172)	LOO-CV	94.3	N, A
Makihara, 2011 [47]	DFT of silhouette + SVD	kNN	OU-ISIR 20m 20f	20-CV	~70-80 (per view)	M (0° -360° +overhead)
Oskuie, 2011 [67]	RTMGEI + Zernike momts.	SVM	CASIA B 93m 31f CASIA B 93m 31f		98.5 98.94	N N, W, C

Under *Test data*, the figure in the bracket is the total number of sequences used.
LOO-CV refers to leave-one-out cross validation.
@ N – side view only M– multi-view (the range of angles are given)
A – various age W – wearing overcoat C– carrying bag

4 Gender Recognition by Body

Here, we refer to the use of the static human body (either partially or as a whole) in an image which, like gait, would be useful in situations where using the face is not possible or preferred. However it is challenging in several aspects. To infer gender, humans use not only body shape and hairstyle, but additional cues such as type of clothes and accessories [71], which may be the similar among different genders. The classifier should also be robust to variation in pose, articulation and occlusion of the person and deal with varying illumination and background clutter.

4.1 Feature Extraction

The first attempt to recognize gender from full body images partitioned the centered and height-normalized human image into patches corresponding to some parts of the body [72]. Each part was represented using *Histogram of Oriented Gradients* (HOG) feature, which was previously developed for human detection in images [73]. HOG features are able to capture local shape information from the gradient structure with easily controllable degree of invariance to translations or rotations [73]. Collins et al. [74] proposed PixelHOG, which are dense HOG features computed from a custom edge map. This was combined with color features obtained from a histogram computed based on the hue and saturation values.

Bourdev et al. [71] used a set of patches they called *poselets*, represented with HOG features, color histogram and skin features The poselets were used to train attribute classifiers which were combined to infer gender using context information. Their method relies on training dataset that is heavily annotated with keypoints.

Biologically-inspired features (BIF) model were used for human body gender recognition by Guo et al. [75]. Only C1 features obtained from Gabor filters were used, as it was found that C2 features degraded performance (as in the case of face gender recognition). Various manifold learning techniques were applied on the features. Best results were obtained by first classifying the view (front, back, or mixed) using BIF with PCA, and followed by the gender classifier.

4.2 Evaluation and Results

Table 3 summarizes the results obtained. Bourdev et al. [71] achieved 82.4 % accuracy but with imbalanced gender dataset. Collins et al. [74] achieved 80.6 % accuracy on a more balanced but smaller dataset with frontal view only. From these results, there is still room for improvement.

Table 3. Body-based gender recognition

First Author, Year	Feature Extraction	Classifier	Training data	Test data	Ave. Acc.%	Dataset variety
Cao, 2008 [72]	HOG	Adaboost variant	MIT-CBCL 600m 288f	5-CV	75	View (frontal, back)
Collins, 2009 [74]	PixelHOG, color hist.	SVM-linear	VIPeR 292m 291f	5-CV	80.62	View (frontal)
Guo, 2009 [75]	BIF + PCA/LSDA	SVM-linear	MIT-CBCL 600m 288f	5-CV	80.6	View (frontal, back)
Bourdev, 2011 [71]	HOG, color, skin pixels	SVM	Attributes of People 3395m 2365f		82.4	Unconstrained

5 Conclusion

In this paper, we have presented a survey on human gender recognition using computer vision-based methods, focusing on 2-D approaches. We have highlighted the challenges and provided a review of the commonly-used features. Good performance has been achieved for frontal faces, whereas for images which include non-frontal poses, there is room for improvement, especially in uncontrolled conditions, as required in many practical applications. Current gait-based methods depend on the availability of one or more complete gait sequences. High classification rate have been achieved with controlled datasets, especially with side views. Investigation of the generalization ability of the methods (through cross database testing) is called for. Performance for datasets containing larger number of subjects with sequences taken under unconstrained environments is not yet established. Some work has also been done based on static human body, but there is scope for further improvement.

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