Computationally Intelligent Gender Classification Techniques: An Analytical Study

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Abstract

Classification has emerged as a leading technique for problem solution and optimization. Classification has been used extensively in several problems domain. Automated gender classification is a significant area of research and has great potential. It offers several industrial applications in near future such as monitoring, surveillance, commercial profiling and human computer interaction. Different methods have been proposed for gender classification like gait, iris and hand shape. However, majority of techniques for gender classification are based on facial information. In this paper, a comparative study of gender classification using different techniques is presented. The major emphasis of this work is on the critical evaluation of different techniques used for gender classification. The comparative evaluation has highlighted major strengths and limitations of these existing techniques. Taking an overview of these major problems, our research is focused on summarizing the literature by highlighting its strengths and limitations. This study also presents several future research areas in the domain of gender classification.

Keywords: *Gender classification, Facial information*

1. Introduction

Digital Image Processing refers to processing the digital image by means of digital computer. In addition to application in other fields, Image Processing techniques are now being used to solve a Variety of problems like image enhancement, study of pollution patterns, improved satellite images and other defense fields. Classification is one of the active research areas of digital image processing. In classification we can classify the total content into limited number of major classes. Classification has broader applications like medical sciences, agricultural sciences and security domains etc. Digital image is an image which has x, y coordinates and amplitude values which are all finite, discrete quantities. A digital image is composed of finite number of elements each of which has particular value and location. These elements are called picture elements or pixels. Many techniques have been used for classification purpose; some of them deal with pixel and some with features. One small face image contains thousands of pixels so the techniques based on pixels are slow, while feature based processing is faster. Generally two types of features are present. These are appearance-based features (also called global features) and geometric-based features (also

called local feature). Global features work with training images while local features are based on geometric features such as nose width and eye brows etc.

Gender Classification is one of the main problems of computer vision. It is an easy task for human to recognize gender but is very difficult for a machine. Gender recognition can be applied in different areas like biometric authentication, security system, criminology and many more. Gender classification plays an important role in face recognition systems. Many techniques have been used in the past years to classify gender including wavelet and random transform [7] and discrete cosine transformation [8] etc.

2. Steps Involved in Gender Classification

Generally Gender classification consists of the following steps. Figure 1 depicts these steps.

- **Preprocessing:** Every face database needs some preprocessing, like normalization of illumination and face detection etc.
- **Feature Extraction**: After performing preprocessing we need to extract face features. Generally two types of features are extracted. Geometric based features and appearance based features.
- **Classification:** Classification is the last step of gender classification in which the face is successfully classified as that of a male or female. For this purpose different types of classifiers are used. e.g. KNN,NN, and SVM.

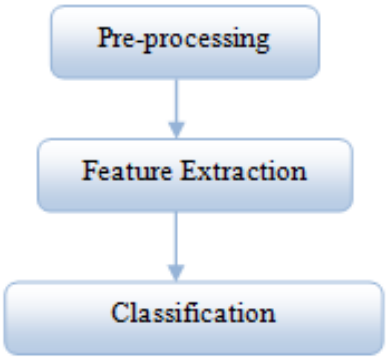


Figure 1. Steps Involved in Gender Classification

3. Approaches to Gender Classification

Gender classification approaches are divided into two categories based on features.These are geometric based features like nose, mouth and size of the eyes and appearance based features which extract the features from the whole face part.

3.1. Geometric Based Features

Brunelli et al. [1] presented geometric based approach. They extract 16 geometric features such as nose, mouth, chin and eyebrow thickness. HyberBF network is trained by using these geometric features which accurately classify gender. Burton et al. [2] reported 94 % accuracy by extracting 73 points from full view face.

3.2. Appearance Based Features

Many appearance based feature extraction approaches involve the role of classifier. Shakhnarovish et al. [3] reported 78 % accuracy by applying Adaboost algorithm to facial images. Baluja and Rowley [4] compared Adaboost with pixels and achieved 93 % accuracy. They claimed that their method is 50 times faster than SVM classifier.

4. Literature Review

The Research on gender classification goes back to the beginning of 1990s. Golomb et al. [5] used multi layer neural network to classify gender. They aligned the face manually for their experiment. First they squeezed 900 unit images into 40 images and then performed classification. They reported 8.1 % classification error rate.

Cottrel et al [6] used Principal component Analysis to reduce the dimension from 4096 to 40, resulting in performance improvement.

Rai and Khanna [7] presented a new approach to classify gender. According to them, gender can be efficiently classified if both Wavelet and Random transform methods are used to extract key features from face. They describe that in order to reduce the data dimensions more, one has to detect the faces from the image and for that purpose knowledge based technique is used to detect faces. After detecting faces, Random and Wavelet transform is used to extract the key features of face so the data is reduced. Random transform is used to compute the projection of an image, decompose the random space of each image up to a third level using Daubecchies (db3) wavelet filter. Results of db3 were in feature vector form which was the input of K-nearest neighbor (KKN) classifier. They compared their results with another features extraction technique discrete cosine transform (DCT). DCT classification rate is less and remains the same if the number of features is increased to like 77%, while proposed method classification accuracy increased when the number of features increased.

Nazir et al [8] suggested that face is a prominent feature for gender classification. They have proposed a new method for classification of gender more efficiently than existing techniques. To make the processing faster they have reduced the dimensions by detecting the face from image using voila Jones technique. Voila and Jones [22] represented image as integral image to make computational process faster. AdaBoost algorithm [23] was used to select key features. Cascade of AdaBoost worked as a classifier through which they discarded the backgrounds from an image. To bring the image lighting effect to its normal form, histogram equalization was performed. As every face image contains some prominent features and to obtain these features, Discrete Cosine Transformation technique (DCT) was implemented. In Nazir et. al., classification work is given to KNN classifier whose work is based on Euclidean distance to find closest neighbors. They have concluded that if the training and testing ratio for KNN classifier is 50 to 50 then accuracy of 99.3% is obtainable. Their results are more accurate compared to Support vector machine (SVM) [19], Neural Networks (NN) [17], and Linear discriminate analysis (LDA) techniques. They argue that Support Vector machine (SVM) achieves 91.10% accuracy while Neural Networks (NN) is 82.30%, LDA 85.80%, and Bayes technique yield 77.62% accuracy.

Jabid et al. [9] state that there are generally two approaches for gender classification. These are the Geometric based and Appearance based feature approaches. Unlike appearance based method which represents whole image as a feature vector, geometric-based method takes more time as these localize eyes and nose etc. The Authors discuss a technique where a face region is divided into small regions. Local directional patterns (LDP) code is figured out from edge response values. Local directional pattern provides strong features to represent the

appearance of the face. For classification they use support vector machine (SVM). SVM tries to find most favorable hyper plane for those problems which are linearly separable. Their proposed method does not deal with pixels intensities hence performs well in the presence of noise and has achieved 95.05% accuracy.

Xu and Lu [10] combine appearance based features (global features) and geometric features (Local features) to enhance the gender classification process. After performing normalization through histogram equalization, (to bring the lighting condition to normal form on image) they pick Haar-like features and then use AdaBoost algorithm to find out strong features which more clearly represent a face. Active Appearance Model (AAM) results in thousands of local features but only those ten features are picked which clearly identify the difference between genders. They describe that there are several methods to normalize the global and local features but due to simplicity they use Min-Max (MM). Proposed method is robust to variation in illumination and poses change.

Mozaffari et al. [11] present a new approach for single image by combining geometric and appearance based features. By using Appearance based features one can get the information of all the regions of the image which is an advantage over the geometric based feature but the disadvantage is that it doesn't oppose when the lighting effect or person expression is changed. Geometric based feature calculate the distance between some specific points thus is sturdy even when the lighting effect or noise is present. Discrete cosine transformation (DCT) and Local binary pattern (LBP) is used to extract the appearance based features. DCT coefficient clearly represents the image so the dimensions are reduced. Local binary Pattern (LBP) was originally introduced for texture description. They suggest that the length of the female face is larger and rounded than the male face. It helps in fitting the ellipse around gender face. Rule is that if the result of discrete cosine transformation and Local binary pattern is not same then gender classification will depend on geometric based features which improve the accuracy by 13 percent.

Jain et al. [12] suggest that although various techniques have been used to identify gender but there does not exist a standard or specific solution to classify gender. The classifier they have used for gender classification is more advanced. They further discuss that a major problem faced by the Digital image processing research is how to represent signals. By using Independent Component Analysis (ICA), they have tried to make the coefficient independent of other data vectors when expanding in linear manner. FERET database containing 250 male & female faces has been used for empirical evaluation. To achieve better results, a different classifier is applied in the lower dimension space. 96% accuracy has been obtained after the application of support vector machine (SVM).

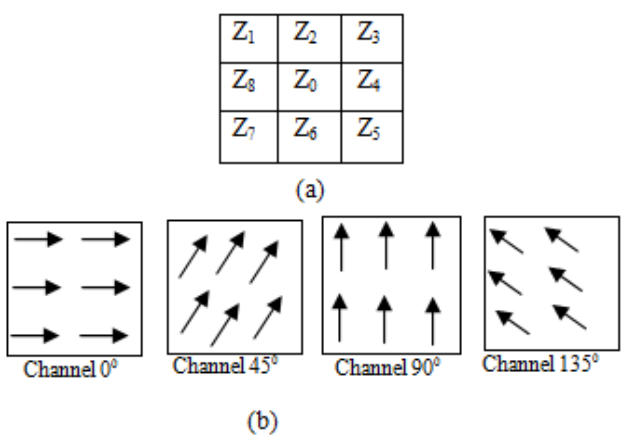
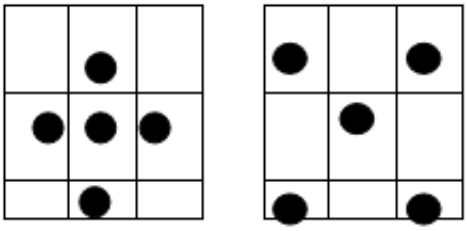


Figure 2. (a) A 3x3 Neighborhood (b) Four Channel IDP Image

Shobeirinejad and Gao [13] evaluate different techniques to extract face features. They suggest that more information can be obtained by using Local Derivative Pattern (LDP) compared to Local Binary Pattern (LBP), which can help in face recognition. Problem with Local derivative pattern is that it represents each pixel with 32 bits which makes processing very slow. They propose Interlaced Derivative Pattern (IDP). This method produces feature vector by extracting distinguishes facial features. The original image is converted into 4 channels, representing four directions that are 0, 45, 90 and 135 degree. Thus this method contains more important information about gender face.

Fang & Wang [14] state that problem with Local Binary Pattern is that if the number of neighborhoods pixels is increased then dimensions also increase. This results in more memory consumption and reduces the pace of the process. They have proposed two methods to improve the LBP features. First is the Low opaque LBP features' fusion. In this method, they divide the neighbors into two category i.e. Cross and diagonal neighbors.



a)Cross neighbor b) Diagonal neighbor

Figure 3. Low Density LBP Operators

After finding LBP codes for both categories, fusion is performed. In second method, they squeeze the LBP features of high density by using Principal component analysis (PCA).The resultant features carry more information and have lower dimensions. FERET face database is used for experiment.

Ravi and Wilson [15] combined face detection with gender classification to produce more accurate results. According to them face detection works as a preprocessor for gender classification. Skin area is detected by converting the RGB image into YCBCR color space; Y represents the luminance while rest represents the color. Thus the performance is not affected by changing the lighting condition. Features of the face like mouth, lip and eyes are detected after converting the image into gray scale. Support vector machine (SVM) of linear form is performed to classify gender. Strength of this method is accurate classification even when the size of image is varied.

Yiding and Ning [16] state that Problem of illumination and angle change in previous techniques has stopped further development of face recognition. To extract face features they propose PCA-SIFT and to classify gender they use FSVM. Scale Invariant Feature Transform (SIFT) extracts the key features and works well under illumination effect. As SIFT identifier has large dimension, so Principal component Analysis (PCA) is used to reduce its dimension. SIFT-PCA is suggested to carry more useful information of gender. For classification Fuzzy support vector machine (FSVM) based on Learning vector quantization (LVQ) is used. The performance of SVM is affected by noise and outliers so by applying fuzzy membership effect of noise and outliers on SVM is minimized. Main task of the LVQ is to find the correct placement of feature vector.

Three face databases are used for experiment. According to them their proposed method results are more accurate and stable.

Sun et al [17] suggest that for gender classification feature extraction is an important task. They think that the performance can be improved sufficiently if one is able to select key features. Different approaches have been used to extract features quality of self-features extraction signify their method from others. PCA which is used to reduce dimension convert the face image into eigenvector, containing different information about gender face. Genetic Algorithm (GA) select features having relevant information about face. Trained Neural Networks (NN) easily classifies gender because of having relevant and small number of features about face. They describe that as a whole they have 18% features, thus error rate of NN classification reduces from 17.7% to 11.3%.

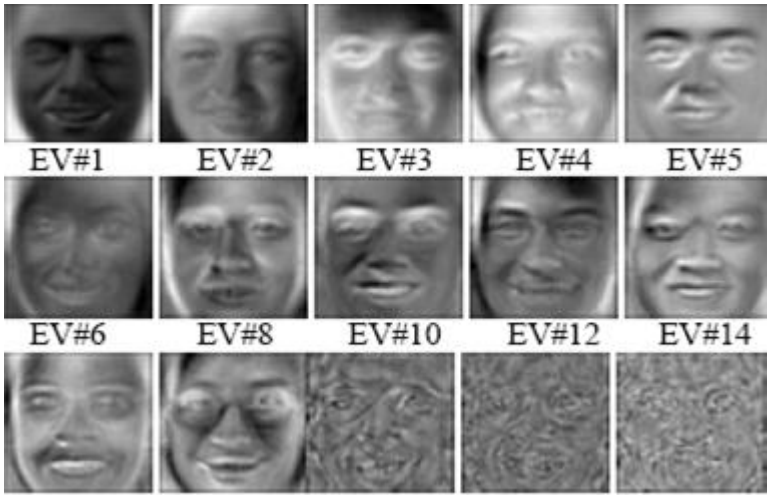


Figure 4. Eigenvectors

Mehmood et al [18] stated that combination of different classifiers provide better results and increase the accuracy than using single classifier to classify gender. They combine different classifiers using weighted majority voting (WMV) technique. Five classifiers named Back propagation neural networks (BPNNC), Fisher linear discriminate (FLD), K-nearest neighbor (KNN), Linear discriminate analysis classifier (LDAC) and support vector machine (SVM) are used. After combination of different classifiers, Genetic Algorithm (GA) is used; this provides most effective union of different classifiers. They apply their technique on Stanford university medical students (SUMS) face database and achieve more accurate results as compared to past techniques. Their face database contained 400 face images, 200 male and 200 female. They applied discrete cosine transform on these images to normalize and then used it as input. They said that 30 % images were used for training purpose and remaining 70% for testing. They compared their results with Genetic algorithm, using principle component analysis (GA-PCA).

Han et al [19] describe that in term of features, two categories of features are available. That are appearance-based features and geometric-based features. In feature based methods the information is extracted from whole image thus is simple and fast as compared with geometric based but when some change in pose occurs then this method become unreliable. Although one loses some information by using geometric feature based method but it is robust to variation in illumination and pose change. Their method

is based on three stages: extract face features, evaluate features and classification. They used 3 dimensional GavabDB erect of triangular network having no makeup and jewelry etc. Geometric based method is used to extract facial features. They place landmarks on face areas like nose, mouth and eyes etc. They study the basic difference between male and female and point out that shape of male eyebrow is straight and also thick as compared to female while female eyebrow is thinner. Female nose is smaller and have small bridge as compared to male. Support vector machine train those geometric features and efficiently classified gender. They describe that error rate indication is 17.44% on average. Their gender face database contained 427 images.

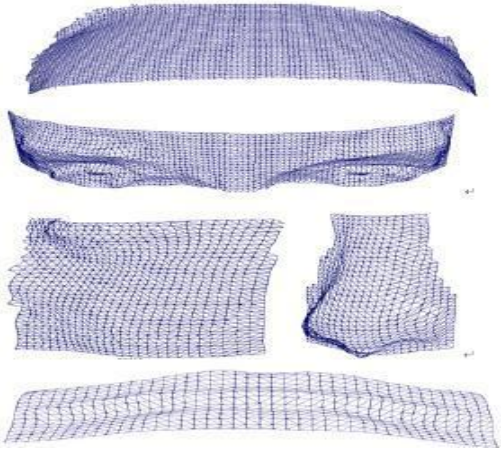


Figure 5. Extracted nose, lip, fore head, Cheek and eye brow region

Ozbudak et al [20] state that as compared to geometric-based features techniques, appearance-based features techniques are faster. They have studied different facial as well as racial information and have noted that some facial features like nose, eyes and forehead contribute more in gender classification process so they mask these features. To enhance the process they first detected the faces using OpenCV (open source computer vision) resize the image to 128x128. PCA is used to exclude the redundant data. Principal component analysis (PCA) reduces dimension and search orthogonal functions (which represent the change in the dataset). Fisher Linear Discriminate (FLD) masks image by making some of pixels black and encoding that information that has changed. This is not orthogonal based. The purpose of FLD is to reduce the data dimension and also perform classification. K-ford cross validation is used to find the accuracy rate of their method. Two sets are used, one to train classifier and one to test the classifier. 480 genders face images, 240 male and 240 female were used for experiment. To obtain more accuracy, frontal images were used for testing purpose. Generated Results indicate those parts of face that contribute more in gender classification process. They suggest that forehead and eyes features contribute more as compared with chin and lip. Experiments are also performed to test weather racial factor has an influence on gender classification. For testing purpose they have used African people images while training set contained Asian and European gender face images. They yielded 93% accuracy rate after performing experiment on FERET and Stanford university face database. After applying their proposed method they noted that classification error rate in case of using Asian people face database is 0% while 13% error rate was noted when using African people faces image. Thus suggesting that

gender of Asian people are more accurately recognized as compared to African peoples. They also noted after experiment that most prominent feature is nose in face.

Chu et al [21] presented new method for gender classification which copes with the barriers like face pose and illumination changes. They describe that the success of the previous methods is based on align faces and those fail when some changes in pose takes place. Rather than using single face image they crop same person's face using various poses and then combine them in set form. Image set is converted to subspace, correlation evaluates the similarity between two sub-spaces. By using Discriminate analysis of canonical correlation (DCC) they find out most accurate gender changeable factors for all face set, which results in better performance on un-align facial images. FERET and MORPH face database is used for experiment.

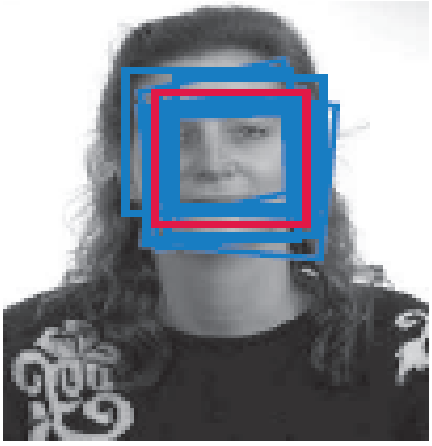


Figure 6. Image set generation by cropping person face from different directions

5. Critical Evaluation

Lit. Ref.	Technique Used	Focus Area	Pros	Cons
[7]	Feature extraction using wavelet and Randon transforms.	Enhancing the performance by efficiently extract features.	Less miss rate, efficiently extracts feature robust to expression and illumination change.	Knowledge based face detection method is time consuming, increase false positive rate due to more general /strict face detection rules.
[8]	Feature extraction using discrete cosine transform (DCT).	Enhancing the performance by reducing the dimensionality of the data set.	Improved classification accuracy and robust to change in illumination.	Face image having pose variation effect the Voila Jones face detection process.
[9]	Representation of the face image using Local directional pattern (LDP)	Enhancing the results by reducing the noise.	More accurate, robust to noise and illumination changed.	Computation process is slower as LDP represent each pixel as eight bit binary code.
[10]	Hybrid approach by combining appearance and geometric based features.	Increasing the performance and accuracy.	Robust to pose and illumination variation.	More time consuming in locating face points and feature extracted.
[11]	Feature extraction from	More accurate result by minimizing the	Classification accuracy improved	Application of Local Binary Pattern (LBP) on larger

	single face image using combination of global and local features.	false positive rate occurs due pose and illumination variation.		window increase dimensionality which results more memory consumption and increase the running time of the process.
[12]	Feature vector representation by using independent component analysis (ICA)	Enhancing the performance by reducing the dimensions.	More accurate results in term of accuracy.	Not robust in illumination and pose changed.
[13]	Feature extraction using Interlaced Derivative Pattern (IDP)	Improving performance by reducing error and increase system speed.	Error reduction, faster and reduced computational complexity compared with Local Derivative pattern (LDP).	Noise and pose variation degrade the computation process
[14]	Feature extraction using Local Binary Pattern (LBP) and Principal Component Analysis (PCA)	Reduce the redundant information of high density LBP features.	Traditional LBP features are improved results in classification accuracy and fast process	Principal Component analysis (PCA) not guarantees that the direction of maximum variance will contain good features for discrimination.
[15]	Feature extraction and classification using Linear support vector machine (SVM)	To produce accurate results irrelevant of image size.	Accurately classify gender faces with different image size.	Non adaptive (static) threshold value for facial feature detection.
[16]	Feature Extraction and classification using Scale Invariant Feature Transform (SIFT) and FSVM	Produce accurate and stable results by reducing the Scale Invariant Feature Transform (SIFT) descriptor dimension	More accuracy, robustness to illumination change	Complexity of classification process increased
[17]	Feature extraction and classification using Principal Component Analysis (PCA) and Neural Networks (NN)	To reduce classification error rate, reduce data dimensions.	Automatic feature subset selection, error rate reduced significantly	Training and selecting the best neural networks take more time.
[18]	Gender classification using Genetic Algorithm (GA) and classifier ensemble	To produce more accurate results	Optimize combination of individual classifier, higher accuracy	Different combination of classifier makes the computation slow, using Genetic Algorithm we won't know to get exact solution.
[19]	Extract face features and classification using geometric based approach and support vector machine (SVM)	Stabilize the performance under pose and illumination change	Robust to illumination and pose change	Selection of SVM appropriate kernel for particular data set effect results.
[20]	Efficient feature extraction for classification using Principal component analysis (PCA)	Find significant face features and make processing fast.	Determining influential parts of face features, Accurate and fast results production	Fisher Linear Discriminant (FLD) suffers from the upper bound on total number of discriminant features.

	and Fisher Linear Discriminant (FLD)			
[21]	Gender classification from un-align facial images	To deal with pose and illumination change	Accurate results	Image containing noise effect in the cropping process, Computation is slow if large dataset is given i.e. subspace of images

6. Conclusion and Future Work

This study deals with the techniques used for gender classification worldwide for more than past two decades.

Generally we are dealing with pixels and features to classify gender. One small image is represented by thousands of pixels. This is why we prefer features to make processing faster. In this paper, a comparison among various gender classification techniques based on features, is presented. Two types of features, global features and local features are used generally. Global features process is faster. Our upcoming work direction entails to contribute in the area of gender classification. The reviews of different techniques which have been used for gender classification disclose that generally these techniques accuracy is high but time consuming. Performance is more enhanced by using better classifier. Similar study of different classifier enlightens us with some significant observations such as; performance is enhanced to combine the classifier. We are intending to develop new technique with the help of literature review.

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