GENDER RECOGNITION FROM FACES USING BANDLET TRANSFORMATION

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ABSTRACT-- *Gender Recognition is important in different commercial and law enforcement applications. In this paper we have proposed a gender recognition system through facial images. We have used a different technique that involves Bandlet Transform instead of previously used Wavelet Transform, which is a multi-resolution technique and more efficiently provides the edges of images, and then mean is combined to create the feature vectors of the images. To classify the images for gender, we have used fuzzy c mean clustering. Experimental results have shown that average 97.1% accuracy have been achieved using this technique when SUMS database was used and 93.3% was achieved when FERET database was used.*

Keywords----- Bandlet, Gender Recognition, Fuzzy C-mean, Multi Resolution.

1. INTRODUCTION

Human face pattern contains a lot of information that is used by human beings to identify among them and for social interaction among people. That information provided by the faces can be categorized in variety of ways including identity, age, gender and much more. One of the most important information gathered from faces is gender because people behaviour to other changes with respect to gender moreover an efficient gender classification technique can significantly increase the performance of different applications that include efficient human to machine interface system, person recognition. It can also be used for several commercial and law enforcement applications including photograph matching in passports, driving license, photo ID's, surveillance in video images. Gender recognition is also very vital because many researches has shown that performing gender recognition prior to facial recognition is termed as the pre-processing step as it is useful to decrease computational load and helps in increasing the speed of the system[1].

Gender recognition is actually a common job for human beings because since from our birth we are able to recognize between mother and father and throughout our life span we are doing gender recognition without even being aware to this fact. Despite of this, the accuracy to recognize gender for human being can decrease surprisingly in particular situations. An online gender recognition test [2] results that the accuracy to recognize gender is just 74%.

Algorithms for gender recognition systems generally involve whole body information in order to achieve all the available information but there are certain scenarios in which whole information is not available or in case camera is so close that just face is being captured, in such cases algorithm is designed that does gender recognition by just using information from faces. There are certain advantages as well as disadvantages of these systems, advantages involve that these algorithms can be implemented in real time systems and disadvantage involve that they are slightly less efficient to the systems that involve complete body information because the information available in faces is far less than that of complete body images.

In the recent times, a lot of research has been started in biometrics, specifically in facial recognition systems [3] because of the increased computational power of recent computers. This advancement is also leading research in gender recognition system that is a specific domain of facial recognition systems.

In this paper we are implementing a different technique that involves multi-resolution technique Bandlets, and mean for feature extraction, after that fuzzy c mean clustering is used to classify the images.

The paper has been arranged as follows. Section III covers the Literature Review, section IV discusses the Proposed Approach, section V includes the Experimental Results, section VI covers Discussion and Future Work while section VII concludes the paper.

2. LITERATURE REVIEW

Gender recognition basically belongs to the class of facial recognition. In facial recognition there are generally three basic blocks as shown in the Figure 1. First of all there is a source of information in case of gender recognition, this source is images from the data sets, second step is feature extraction. This process is applied on each and every image from the data set, after that the last step is the classifier that classifies the feature vectors on the basis of their features.

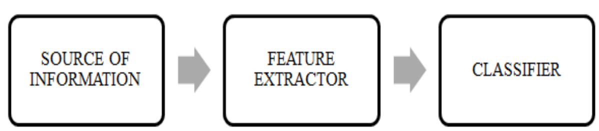

Figure 1 A general scheme for facial recognition systems.

There are basically two main types of approaches for feature extraction one is the statistical approach and the other one is geometry feature based method. Statistical approach involves the statistical investigation to select the most important features in the images. The main drawback of this approach is that in order to create a pattern, this approach requires a large number of input data. The geometry feature based methods use the relationship of the facial components like nose, mouth, ears etc.

For a classification, the classifier plays the most important part because it has to choose most important features to classify into the separate classes, in case of gender recognition there are two classes one is male and the other is female.

There are so many methods that have been proposed in literature for gender recognition using facial information. Different techniques involve LBP [4], support vector machines (SVM)[5], weber local descriptor (WLD)[6], discrete wavelet transform (DWT)[7], principal component analysis (PCA)[8] and interlaced derivative pattern (IDP)[9]. Some techniques also involve the combination of two techniques to improve the results.

Different databases have been used for the classification of gender from facial images including face recognition technology (FERET) [10], www facial images, face recognition grand challenge (FRGC), CAS-PEAL, Caltech and CMU databases have been used in different papers for gender recognition.

The main draw back with all the previous approaches is the lack of multi resolution technique. In this paper we are using Bandlets + mean for the feature extraction purpose and after that fuzzy c mean clustering technique is used for the classification of gender.

In this technique first the input image is decomposed into several sub-bands of different scales, each sub-bands is then divided into blocks and after that mean is calculated on each block, then these means are used to create a feature vector of the image.

Bandlet is the technique that uses multi resolution features of images because image contains many geometric structures that carry different information, these geometric structures can be used to improve the representation of image. Wavelet transform is one of the techniques that can be used for geometric representation but it lacks where it comes sharp transitions in images. Carlson in [11] proposed a technique for edge based image representation which represented the jumps across curves in images. An image approximation was then achieved by calculating the jumps across edges in the image. Many different edge based image representation algorithms are based on similar idea with different edge detection procedures and jump models.

Global optimization procedures have also been proposed for edge detection [12], and then over quad trees using fast dynamic programming algorithms, image segmentation over dyadic squares is computed.

A difficulty that was faced in all these edge detection techniques was that these techniques do not correctly represent sharp image transitions i.e. no discontinuity is found in edges jump. Moreover, optical diffraction blurs the grey-level discontinuities across the boundaries and on other hand, much sharp transitions are produced due to texture variations. So current edge based algorithms do not exceed in performance as compared to orthogonal wavelets approximation, especially in complex images.

Candes and Donoho in [13] proposed that a non-adaptive representation can be constructed that takes advantage of geometric regularity of image by the decomposition in fixed basis or curvelets. These families are composed of functions that define basis of $L^2(R^2)$. Donoho and Candes proposed that an approximation f_M with M curvelets of an image of which have discontinuities along C^2 curves produce an error that satisfies the equation:

$$\| f - f_M \|^2 \leq CM^{-2} (\log_2 M)^3 \quad (1)$$

So this approach is very ill mannered because it deals with the representation of the image with edges so instead of using this approach we represent image with geometric flow of vectors using Bandlet approach. If the image has regular variations, these vectors provides the local directions, these orthogonal Bandlet bases are created by sub dividing image into the blocks where the geometric flow is parallel.

PROPOSED APPROACH

There are three main step of our system for gender recognition first one is data acquisition from the data set, the second one is making features with and third one is categorization of the facial images with respect to the gender. Block diagram of proposed scheme is shown in Figure 3.

The Bandlet basis are created by using wavelet basis which are enveloped along the flow of the geometry as shown in figure 2 which helps in taking advantage of the image regularity, there are certain conditions that are applied on the geometry to obtain orthonormal Bandlet basis. When applying Bandlet transform, the image is divided into different square blocks with varying resolution. In each block (Ω_i) there must be at least one contour specifying the edge in that block within the flow of the geometry. If there is no contour in that block, it means that image intensity is regular and uniformly distributed in that block after that when we compute wavelet basis and approximate those basis in $L^2(\Omega)$ domain, the Bandlet basis are computed.

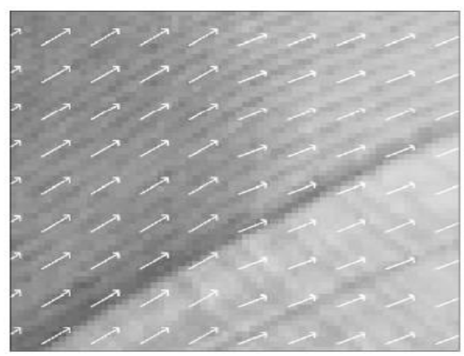

Figure 2. Bandlet segmentation in which each arrow is showing the flow of the vector in each region.

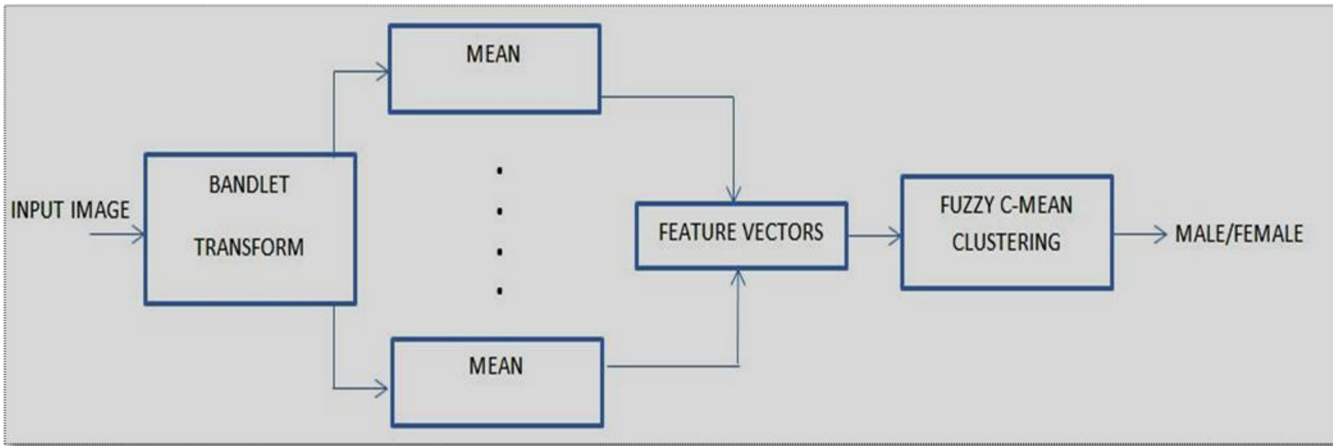

Figure 3. Block diagram of the proposed scheme

$$\left.\begin{cases} \emptyset_{j,m}(x) = \emptyset_{j,m1}(x1)\emptyset_{j,m2}(x2) \\ \psi^{H}_{j,m}(x) = \emptyset_{j,m1}(x1)\psi_{j,m2}(x2) \\ \psi^{V}_{j,m}(x) = \psi_{j,m1}(x1)\emptyset_{j,m2}(x2) \\ \psi^{D}_{j,m}(x) = \psi_{j,m1}(x1)\psi_{j,m2}(x2) \end{cases}\right\} (j, m1, m2) \in I_{\Omega} \quad (2)$$

Where wavelets transform ψ (t) with expansion j and translation k is calculated by taking product of elementary orthogonal operators and the result is produced as follows.

$$\psi_{j,k}(t) = 2^{\frac{-j}{2}}\psi(2^{-j}t - k) \quad (3)$$

$$\emptyset_{j,k}(t) = 2^{\frac{-j}{2}}\psi(2^{-j}t - k) \quad (4)$$

In the above equation I_{Ω} shows the index geometry set of the block Ω, $\emptyset_{j,m}(x)$ is the rough scale calculation, $\psi^{H}_{j,m}(x)$ denotes high horizontal frequency, $\psi^{V}_{j,m}(x)$ denotes high vertical frequency,

$\psi^{D}_{j,m}(x)$ denotes high diagonal frequency coefficients that are decomposed by discrete wavelet transform. After that to compute Bandlet orthonormal basis in geometric flow of region Ω in equation 2, Wavelet basis will be replaced as follows.

$$\left.\begin{cases} \emptyset_{j,m}(x) = \emptyset_{j,m1}(x1)\emptyset_{j,m2}(x2 - c(x1)) \\ \psi^{H}_{j,m}(x) = \emptyset_{j,m1}(x1)\psi_{j,m2}(x2 - c(x1)) \\ \psi^{V}_{j,m}(x) = \psi_{j,m1}(x1)\emptyset_{j,m2}(x2 - c(x1)) \\ \psi^{D}_{j,m}(x) = \psi_{j,m1}(x1)\psi_{j,m2}(x2 - c(x1)) \end{cases}\right\} j\ m > j\ m1\ m2 \quad (5)$$

When we insert the Bandlet in wrapped Wavelet basis the equation becomes as follows

$$\left.\begin{cases} \emptyset_{j,m}(x) = \emptyset_{j,m1}(x1)\emptyset_{j,m2}(x2 - c(x1)) \\ \psi^{H}_{j,m}(x) = \emptyset_{j,m1}(x1)\psi_{j,m2}(x2 - c(x1)) \\ \psi^{V}_{j,m}(x) = \psi_{j,m1}(x1)\emptyset_{j,m2}(x2 - c(x1)) \\ \psi^{D}_{j,m}(x) = \psi_{j,m1}(x1)\psi_{j,m2}(x2 - c(x1)) \end{cases}\right\} (j,m1,m2) \in I_{\Omega} \quad (6)$$

In the above equation c(x) is defined as the flow line of the geometry changes of the translation parameter that changes with the geometry changes and it is expressed as

$$c(x) = \int_{x\,min}^{x} c\,(u)du \quad (7)$$

It has also been observed that the size of the division that we use while dividing the image affects the direction of geometric vector flow, if we use smaller block size then Bandlet function can accurately define the edges available in that block. The change in edges with the variation in number of blocks can be observed in the figure 4 (a) showing the original image (b) showing the image with smaller block size and 16x16 resolution and (c) showing slightly larger block size with 8x8 resolution. It can be seen that when we use smaller block size the number of blocks increases which results in large number of edges and the geometry flow is smooth while when we increase the block size it decreases the number of blocks in the image and that results in reduced number of edges which results in slightly coarse image representation.

After the Bandlets have been implemented on our data set images, the next step that comes is the calculation of mean on each block. Then combining the means of all the blocks makes the feature vector of that image.

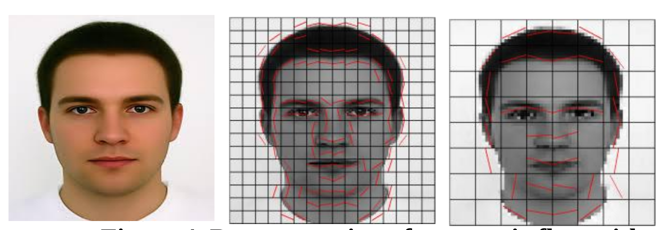

Figure 4. Representation of geometric flow with different block sizes (a) original image, (b) 16x16 small block size, (c) 8x8 large block size.

As Bandlet transformed images provide the contours where there are edges so in order to efficiently create features we used this statistical approach to distinguish between male and female images using facial specifications.

After obtaining the feature vectors the next step is to classify the images by using those feature vectors, we have used fuzzy c mean clustering for the classification of the images. In fuzzy clustering each point of the feature vectors has a chance of associating to any cluster instead of belonging to just single cluster, so the points at edges can belong to the cluster of less degree instead of belonging to the centre one.

In fuzzy c mean clustering any point has coefficients that describes the degree of that point belonging to certain cluster. By using fuzzy c mean clustering the centre of the cluster is obtained by calculating the mean of all the points. And then distance is measured with each centre vector to the vector of the image in feature vector, after that it is assigned the cluster, in our case as we are classifying gender there will be 2 clusters one for male and other for female. Equation shows the centre of each cluster.

$$c_k = \frac{\sum x w_k(x)^m x}{\sum x w_k(x)^m} \quad (11)$$

A point x has different set of coefficients that gives the degree of being in the k^{th} cluster $w_k(x)$. by using fuzzy c-means, the centroid of a cluster is the mean of all points that is weighted by their degree of belonging to the specific cluster.

3. EXPERIMENTAL RESULTS AND DISCUSSION

To experiment with the method given in previous section, we selected 3 different tests to perform. These tests and the data base used in the experiments are explained below.

A. Database

We have used SUMS and FERET databases in our experiment. SUMS database contains 400 images, out of which 200 are male and 200 are female, each of 200 x 200 resolutions. All images are of good quality and are greyscale. Images have different poses and varying facial expressions. Images also contain people of different ages, with and without hair, with and without glasses and having different ethnic backgrounds while FERET has 1564 sets of images.

B. Test setup

Results of our proposed technique have been compared with previously known techniques. Features have been extracted as follows. In our experiment, we have applied Bandlet on all images of database then these Bandlet transformed images were subtracted from original images. These difference images have been divided into different size blocks. In this experiment 8x8, 4x4 and 2x2 blocks have been made. When image is divided into 64 blocks, mean is calculated on each block. Hence, each block corresponds to a mean value. Blocks on black portion correspond to zero mean value while blocks corresponding to edges result in some non-zero value. These 64 mean values from 64 blocks, 16 mean values from 16 blocks and 4 mean values from 4 blocks are concatenated to make 84 entities feature vector of the image. Feature vectors of all the images from the database are generated and stored in a matrix. Fuzzy c-mean clustering is applied on these feature vectors using 2 clusters and results are achieved. Average 97.1% accuracy was achieved when SUMS database was used and 93.3% was achieved when FERET was used. Set of original images and Bandlet transformed images have been given in Figure.8. In the experiment whole database was our test set.

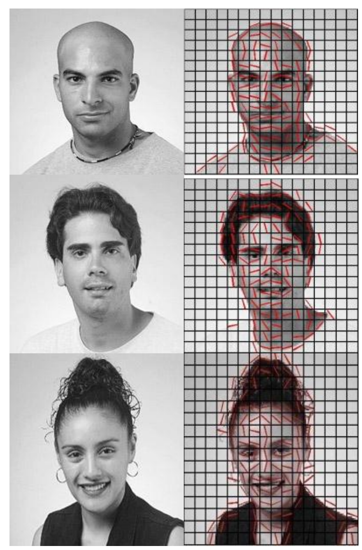

Figure. 8. Original and transformed images

Table 1. Comparison of gender recognition techniques with accuracy

Authors	Feature Extraction Technique	Classifier Used	Test Database	Average Accuracy (%)
Lee [14]	Regression function	SVM	WEB Images	81.1
Demirkus [15]	SIFT	Bayesian	Video Sequence	90
Li [16]	DCT	Spatial GMM	YGA	92.5
Aghajanian [17]	Patchbased	Bayesian	Web images	89
Xu [18]	Haar-like, fiducial distances	SVM-RBF	5-CV	92.38
Makinen [19]	Various -pixels, LBPH, Haar-like	Mix	FERET web images	92.86 83.14
Lian [20]	LBP histogram	SVM polynomial	CAS-PEAL	94.08
Baluja [21]	Pixel comp.	SVM	5-CV	93.5
Buchala [22]	PCA	SVM –RBF	5-CV	92.25
Shakhnarovich [23]	Haar-like	Adaboost	5-CV	79

			Video seqs.	90
ErnoMäkinen [24]	LBP	Neural Network	FERET	91.11
ErnoMäkinen [24]	LBP	SVM	WWW	66.90
ErnoMäkinen [24]	LBP	SVM	FERET	73.88
ErnoMäkinen [24]	LBP	SVM	FERET	71.33
ErnoMäkinen [24]	LBP	SVM	WWW	76.01
Ours	Bandlet + mean	Fuzzy c-mean	SUMS	97.1
Ours	Bandlet + mean	Fuzzy c-mean	FERET	93.30

[25] has compared different techniques for gender recognition, our results compared with previous techniques have also been tabulated in Table 1. It has been observed that when our proposed technique was compared with previously proposed techniques such as SVM, Threshold Adaoost, LUT Adaboost, Mean Adaboost, LBP+SVM, PCA (compared in [24]), gives more accurate results. The comparison has been shown in Figure 9.

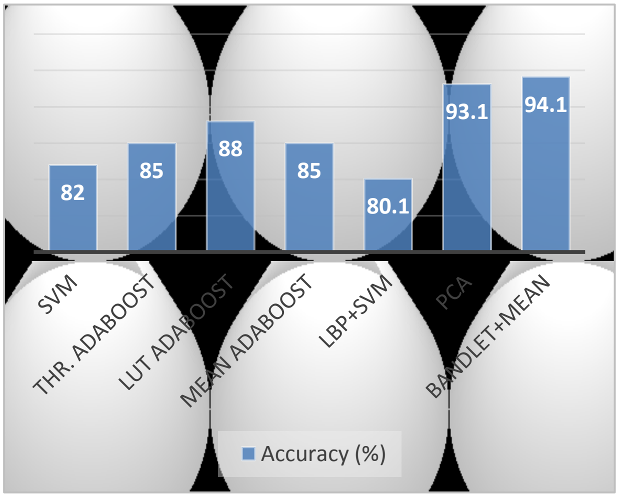

Figure 9a. Comparison graph for SUMS

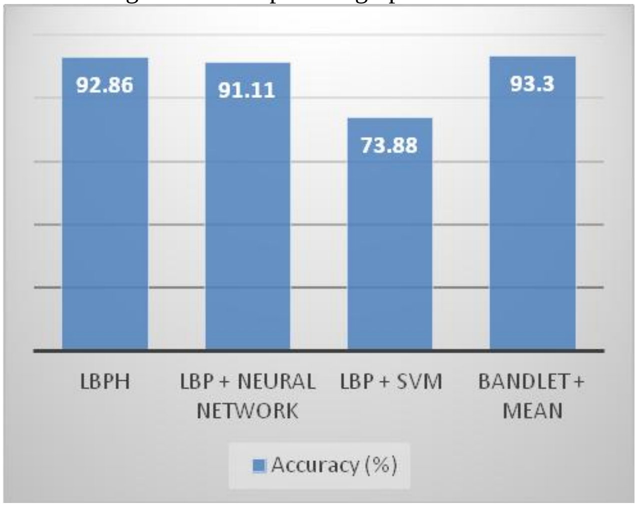

Figure 9b. Comparison graph for FERET

As verified in last section, proposed algorithm is more efficient and improved results have been achieved as compared to previously known algorithms. Maximum of 97.1 % average accuracy has been achieved. Actually, instead of Wavelet Transform, Bandlet Transform has been used in this approach, which efficiently represents the geometric flow across the edges of the image. So, Bandlet Transform is better for extracting the geometrical properties of the images which resulted in better and improved performance of our proposed algorithm.

CONCLUSION AND FUTURE WORK

This research carried out experiments and observations that our proposed technique, when compared with previously renowned techniques, was also more efficient. The maximum average accuracy achieved was 97.1%. In our experiment, we have used face database as it is, without any pre-processing. While in authors first perform face detection algorithm on the whole database and discard those images which are not detected by the algorithm. After performing face detection, gender recognition techniques are applied which result in more accurate results. So, in future our achieved results can be more improved by pre-processing steps that is by 1st applying face detection algorithm on the database and discarding those images which are not detected by the algorithm and then applying the proposed (Bandlet + mean) technique.

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