### Gender Recognition from Face Images with Dyadic Wavelet Transform and Local Binary Pattern

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**Abstract.** Gender recognition from facial images plays an important role in biometric applications. We investigated Dyadic wavelet Transform (DyWT) and Local Binary Pattern (LBP) for gender recognition in this paper. DyWT is a multi-scale image transformation technique that decomposes an image into a number of subbands which separate the features at different scales. On the other hand, LBP is a texture descriptor and represents the local information in a better way. Also, DyWT is a kind of translation invariant wavelet transform that has better potential for detection than DWT (Discrete Wavelet Transform). Employing both DyWT and LBP, we propose a new technique of face representation that performs better for gender recognition. DyWT is based on spline wavelets, we investigated a number of spline wavelets for finding the best spline wavelets for gender recognition. Through a large number of experiments performed on FERRET database, we report the best combination of parameters for DyWT and LBP that results in maximum accuracy. The proposed system outperforms the stat-of-the-art gender recognition approaches; it achieves a recognition rate of 99.25% on FERRET database.

1 Introduction

Category specific approach for face recognition can perform better but the bottleneck for this approach is categorization i.e. to categorize the facial images into different categories based on visual cues like gender and race. In this paper, we address the problem of face categorization based on gender i.e. gender recognition problem. Gender recognition is important due to other reasons as well; it can increase the performance of a wide range of applications including identity authentication, search engine retrieval accuracy, demographic data collection, human-computer interaction, access control, and surveillance, involving frontal facial images.

Many techniques have been used for extracting discriminative features from facial images, which are given to a binary classifier. The feature extraction step is done through either geometric or appearance based methods. In previous methods geometric features like distance between eyes, eyes and ears length, face length and width, etc. are considered. Whereas in appearance based methods image as a whole is considered rather than taking features from different parts of a face as local features. To deal with the problem of high dimension, some researchers used Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA). For classification, different techniques like neural network, nearest neighbor method, LDA and other binary classification techniques have been used..

Techniques like Artificial Neural Networks (ANNs) [1] and [2] and Principal Component Analysis (PCA) [3] were first used for gender classification. A Hybrid technique was proposed by Gutta et. al. [4] consisting of an ensemble of Radial Basis Functions and C4.5 decision trees. Another method proposed in [5] achieved the recognition rate of 96% on FERRET database. SVMs were used by Moghaddam et. al. [6] for gender classification; they reported 3% of misclassification on the color FERET database. Neural Network was exploited by Nakano et. al. [7] for the information extracted from edges of facial images for gender recognition. Lu et. al. [8] used SVM to exploit the range and intensity information of human faces for ethnicity and gender identification. Not only sophisticated classifiers but simple techniques were also used for gender recognition. Yang et. al. [9] improved gender classification using texture normalization. Gaussian Process Classifier is used by Kim et al. [10] in their proposed system for gender recognition.

Several weak classifiers were combined by Baluja and Rowley [11] for pixel value comparisons on low resolution gray scale images in their AdaBoost based gender classifier. They used normalized images of size 20x20 in their test performed on FERET database, which showed an overall recognition rate of 90%. Lu and Shi [12] employed the fusion of left eye, upper face region and nose in their gender classification approach. Their results showed that their fusion of face region approach outperforms the whole face approach. Extending this idea, Alexandre [13] used a fusion approach based on features from multiple scales. They worked on normalized images of resolutions (20 x 20, 36 x 36 and 128 x 128) to extract shape and texture features. For texture features, they used Local Binary Pattern [14] approach.

DyWT decomposes the image features at different scales into different subbands which makes the analysis easy. DWT transform has been used for face description but it does not have better potential for features extraction because of being translation invariant. DyWT is translation invariant and is a better choice for face description. On the other hand, LBP captures local detail in a better way. Employing both DyWT and LBP in a novel way, we present a new face description technique. This approach outperforms the state-of-the-art techniques.

The rest of the paper is organized as follows. Section 2 presents an overview of Dyadic wavelet Transform (DyWT). In Section 3 Spatial Local Binary Pattern is discussed in detail. Gender recognition system based on our methodology is discussed in Section 4. Section 5 presents experimental results and their discussion. In the last Section 6, paper is concluded.

2 Dyadic Wavelet Transform

In this paper Dyadic Wavelet Transform (DyWT) is used for face description. Unlike DWT, it is translation invariant and can capture the micropatterns like edges in a better way. In the following paragraphs, we give an over view of DyWT. Complete detail can be found in [15].

DyWT wavelet transform involves two types of bases functions: scaling and wavelet functions. A scaling function satisfies the following two-scale relation:

. (2.1)

Its Fourier Transform (FT) satisfies the following relation:

(2.2)

Using the scaling function (*t*), define a function with the following relation:

Its Fourier transform is given by

(2.3)

The function is called dyadic wavelet transform if for some , if it satisfies the following inequality:

Projection of any L2 function on dyadic wavelet space requires that the reconstruction

condition must be satisfied, which further needs corresponding dual scaling and dual wavelet functions. The dual scaling function is defined by the following two-scale relation:

,

and the dual wavelet function satisfies the following two scale relation:

.

The Discrete Fourier Transform (DFT) of the filters are denoted by respectively. These filters are dyadic wavelet filters if the following condition is satisfied:

(2.4)

The by symbol (\*) denotes the complex conjugation. The above condition is called the reconstruction condition for dyadic wavelet filters.

**Theorem 1**. (Algorithm) the reconstruction condition (2.4) is used to obtain the following decomposition formulae

(2.5)

(2.6)

where is given by , and the following reconstruction formula

(2.7)

Equations (2.5) and (2.6) define the Fast dyadic wavelet transform (FDyWT) and are used for projection of 1-d function onto the space of dyadic wavelets. In case of 2-d function i.e. images, the projection is obtained by applying FDyWT in x-axis (horizontal) and then in y-axis (vertical) direction. Equation (2.7) defines the Inverse dyadic wavelet transform (IDyWT).

Spline dyadic wavelets are dyadic wavelets. A family of spline dyadic wavelets is defined with wavelet filters k] and whose Fourier transforms are given by:

(2.13)

(2.14)

where denotes the degree of the box-spline and



and



The degree *r* is independent of *m*. Different values of r and m defines a family of spline dyadic wavelets. In this paper we explore this family for face representation for gender recognition.

3 Spatial Local Binary Pattern (SLBP)

LBP descriptor computed using LBP operator introduced by Ojala et al. [16] is one of the widely used texture descriptors that have shown promising results in many applications [14], [17], [18], and [19]. Ahonen et al. [20] used it for face recognition, Lian and Lu [21] and Sun et al. [13] employed it for gender recognition. The initial LBP operator associates a label with each pixel of an image; the label is obtained by converting each pixel value in the 3x3-neighbourhood of a pixel into a binary digit (0 or 1) using the center value as a threshold and concatenating the bits, as shown in Figure 1. Later the operator was extended to general neighborhood sizes, and its rotation invariant and uniform versions were introduced [14].



Figure : LBP Operator

The general LBP operator is denoted by and is defined as follows:

(3.1)

where P is the total number of pixels in the neighborhood and R is its radius, pc is the center pixel and the thresholding operation is defined as follows:

(3.2)

Commonly used neighborhoods are (8, 1), (8, 2), and (16, 2). The histogram of the labels is used as a texture descriptor. The histogram of labeled image is defined as:

(3.3)

where *n* is the number of different labels produced by the LBP operator and

(3.4)

Figure 2 shows the histogram extracted from an image with LBP operator. An LBP histogram in this approach contains information about facial micro-patterns like the distribution of edges, spots and flat areas over the whole image. In case of (8, R) neighborhood, there are 256 unique labels, and the dimension of LBP descriptor is 256. The basic LBP histogram is global and represents the facial patterns but their spatial location information is lost. .



Figure 2: LBP Histogram Calculation for Full image



Figure : LBP Histogram generation by Proposed Technique

To overcome this issue, spatially enhanced LBP histogram is calculated. Figure.6 shows the process of computing spatially enhanced LBP histogram. An image is divided into blocks; LBP histogram is calculated from each block and concatenated.

General LBP operator has three parameters: circular neighborhood (P, R), rotation invariance (ri) and uniformity (u2). For a particular application, it is necessary to explore this parameter space to come up with the best combination of these parameters. In this Paper we will explore Uniform version of LBP with P and R as 8 and 1.

4 Gender Recognition

The proposed system for gender recognition follows the general architecture of a recognition system i.e. it consists of four main parts: pre-processing, feature extraction, feature selection and classification. Various existing systems differ in the choice of feature extraction and classification techniques. Preprocessing step involves the normalization of face images. We introduced a new method for feature extraction based on LBP and DyWT. Further we apply feature subset selection method to increase accuracy and to reduce the time complexity. Simplest minimum distance classifiers based on L1, L2, and CS distance classifiers are used.

The block diagram of the recognition system which we used for gender recognition is shown in Figure 4.



Figure : Gender Recognition system

4.1 Feature Extraction

For feature extraction, we used SLBP and DyWT. DyWT decomposes an image in to a number of sub-bands at different scales. Figure 6 shows an image which is decomposed using DyWT up to scale 2. After decomposition SLBP operation is used to extract features from each sub-band.



Figure Example of image from FERET database in to sub-bands

Specifically the following steps are used to extract features from each face:

1. Normalize the image
2. Decompose the image with DyWT up to scale N
3. Apply SLBP on each sub-band
4. Concatenating SLBP histograms for each subband, a multiscale LBP histogram is generated.

These steps have been shown in Figure 6.

DyWT parameters involve scales and filters. These filters are made from the combination of the spline values R and M as mentioned in section 2. SLBP involves many parameters: Neighborhood P, Radius R, Mapping, and block sizes. By experiment we found the best set of parameters which produces maximum result. The dimension of the features becomes big in some cases. TO reduce the dimension and to enhance the accuracy, we apply SUN’s FSS algorithm [22].



Figure 6 Proposed Methodology

4.2 Classifier

In our system we preferred to employ minimum distance classifiers for achieving maximum accuracy for gender recognition and keeping the system simple. SLBP and DyWT with FSS can give better or comparable results to many stat-of-art techniques using city block distance (L1), Euclidean Distance (L2), and Chi-Square (CS). The accuracy of a gender recognition system depends on the choice of a suitable metric.

5 Experiments and Discussion

We performed experiments on FERRET database [5], which is one of the challenging databases for face recognition. Each image is normalized and cropped to the size 60x48 pixels. The database contains frontal, left or right profile images and could have some variations in pose, expression and lightning. In our experiments, we used 2400 images of 403 male subjects and 403 female subjects taken from sets fa and fb. We used 1204 (746 male+458female) images for training and 1196 (740 male + 456 female) images for training. Some images taken from FERET database are shown below.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |

We tested the LBP variants with uniform mapping, no mapping and P = 8, & R = 1. Further, two types of histograms were calculated: normalized and simple. For SLBP, each was divided into blocks of sizes 15x12, 12x12, and 10x12. We tested DyWT with decomposition up to level 5 i.e. with sub-bands LL, LH1, HL1 …, HH5. In addition, we tested different spline dyadic wavelets with m = 0, 1, 2, 3, 4, and r = 1, 2. To reduce the dimension of the feature space, we used SUN’s [24] FSS algorithm.

In our experiments, SLBP with block size 10x12, uniform mapping, and simple histogram gives the best result (98.66%) when L1 minimum distance classifier is used. The effect of block sizes is shown in Figure 7. In [13], LBP with uniform mapping and block sizes of 16x16 and 32x32 were used which resulted in recognition rate of 93.46% as shown in Figure 8. It is noted in the experiments that smaller block sizes increase accuracy but also increase number of features, which increases time complexity. Due to this reason, we used SUN’s algorithm to reduce the number of features and time complexity.



Figure 7: Effect of Block Sizes for Proposed technique in comparison to [13]



Figure 8: Best results of proposed techniques

DyWT with wavelet filters with r = 1, and m = 1, gave the best (96.74%, see Figure 7) result with subband LH3 at scale 3. The effect of different filters can be seen in Figure 9, it shows the best accuracy in each case. Figure 7 indicates that when SLBP is used to extract features from subbands obtained with DyWT, there is significant improvement; FSS further improves the result.



Figure : Effect of different Filters on decomposed images

We compare our method with the stat-of-the-art techniques like Local Gabor Binary Pattern with LDA and SVMAC (*LGBP-LDA SVMAC*) [23], Local Gabor Binary Pattern with LDA and SVM *(LGBP-LDA SVM*) [23], and Multi-resolution Decision Fusion method (*MDF*) [13]. The results shown in Figure 10 indicate that the proposed system yields better recognition results.



Figure : Comparison of our results with stat-of-art techniques

6 Conclusion

We addressed the problem of gender recognition from facial images in this paper, and proposed a new technique for face description that is based on DyWT and LBP. The proposed techniques lead to a better recognition accuracy of 99.25%. There are many parameters to be tuned properly. We found that block size of 12x12, uniform mapping and neighborhood (8, 1) for LBP and LH3 subband of DyWT with wavelet filters r = 1 and m = 1 yield the best accuracy (99.25%). This result is further enhanced by FSS. A comparison with the stat-of-the-art methods indicate that the proposed method performs better than all methods published so far. It is first time that we explored spline dyadic wavelets for gender recognition problem. In our future work, we will explore DyWT and SLBP with sophisticated classifiers like SVM.

Acknowledgement

This work is supported by the National Plan for Science and Technology, King Saud University, Riyadh, Saudi Arabia under project number 10-INF1044-02.

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