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GENDER RECOGNITION FROM FACE IMAGES WITH DYADIC WAVELET TRANSFORM AND LOCAL BINARY PATTERN

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Gender recognition from facial images plays an important role in biometric applications. Employing Dyadic wavelet Transform (DyWT) and Local Binary Pattern (LBP), we propose a new feature descriptor DyWT-LBP for gender recognition. DyWT is a multi-scale image transformation technique that decomposes an image into a number of sub-bands which separate the features at different scales. DyWT is a kind of translation invariant wavelet transform that has a better potential for detection than Discrete Wavelet Transform (DWT). On the other hand, LBP is a texture descriptor and is known to be the best for representing texture micro- patterns, which play a key role in the discrimination of different objects in an image. For DyWT, we used spline dyadic wavelets (SDW). There exist many types of SDW; we investigated a number of SDWs for finding the best SDW for gender recognition. The dimension of the feature space generated by DyWT-LBP descriptor becomes excessively high. To tackle this problem, we apply a feature subset selection (FSS) technique that not only reduces the number of features significantly but also improves the recognition accuracy. Through a large number of experiments performed on FERET and Multi-PIE databases, we report for DyWT- LBP descriptor the parameter settings, which result in the best accuracy. The proposed system outperforms the stat of the art gender recognition approaches;

it achieved a recognition rate of 99.25% and 99.09% on FERET and Multi-PIE databases, respectively.

Keywords: Gender recognition; feature extraction; feature subset selection; FERET; multi-PIE.

1. Introduction

Category specific face recognition approach first categorizes the faces into different categories based on visual (race, gender etc.) and non-visual cues and then uses category specific feature descriptors for face classification.[27] The bottleneck for this approach is categorization. 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.

The main components of a gender recognition system are feature descriptor and classification technique. Many techniques have been used for extracting discriminative features from facial images, which can be broadly classified into geometric and appearance based methods; in the former category, geometric features like distance between eyes, eyes and ears length, face length and width, etc. have been employed. On the other side, in appearance based methods the whole image is considered rather than taking features from different parts of a face. In the second category, the dimension of the feature space usually becomes very high, and to deal with the problem of the curse of dimensionality, some researchers have proposed feature transformations like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Appearance based approach addresses the facial textures and has proven to be better than geometric approach.[29] In this paper, we propose a new appearance based method, which employs Dyadic Wavelet Transform (DyWT) and Local Binary Pattern (LBP) for the representation of facial images. DyWT represents a facial image at various scales and LBP is a state of the art texture descriptor. DyWT decomposes an image at different scales into different sub-bands, which makes the analysis easy. DWT transform has been used for face description but it does not have better potential for feature extraction because of not 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 develop a description of facial images for the problem of gender recognition. The dimension of the feature space becomes very high, which not only adds to the time complexity of the recognition system but also degrades the recognition accuracy due to redundant features. To overcome this problem, we employ stat of the art best feature subset selection algorithm. For classification we used minimum distance classifier with city-block distance (L1). For validation we used two public domain databases: FERET and Multi-PIE. The proposed system for gender recognition outperforms the existing systems. Initially, this idea was presented in Ref. 28. The main contributions of the paper are as follows:

- A novel feature descriptor based on DyWT and spatially enhanced Local Binary Pattern (SLBP) for facial image representation. It encodes multi-scale texture microstructures and thus it has better discriminatory potential.
- Investigation of dyadic wavelet filters and the scales in DyWT decomposition, which result in better DyWT-SLBP feature descriptor.
- A novel gender recognition system based on DyWT-SLBP features and a locally leaning based feature subset selection technique that has recognition rate of 99.25% on FERET database and 99.09% on Multi-PIE database.

The rest of the paper is organized as follows. Section 2 presents related work for gender recognition. An overview of Dyadic wavelet Transform (DyWT) is given in Section 3. Spatially-enhanced Local Binary Pattern (SLBP) is discussed in detail in Section 4. Gender recognition system based on our methodology is described in Section 5. Section 6 presents experimental results and discussion. Section 7 concludes the paper.

2. Related Work

In this section, we give an overview of the techniques, which have been proposed so far for gender recognition. Techniques like Artificial Neural Networks (ANNs)[1,2] 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. Smirg *et al.*[5] proposed a system using PCA and DCT for dimensionality reduction, genetic algorithm for selecting a representative image and nearest neighbor classifier with neural network for gender recognition. The recognition accuracy was not promising i.e. 85.9%. Another method proposed in Ref. 5 achieved the recognition rate of 96% on FERET database. SVMs were used by Moghaddam *et al.*[7] for gender classification; they reported 3% of misclassification on color FERET database. Neural Network was exploited by Nakano *et al.*[8] for the information extracted from edges of facial images for gender recognition. Lu *et al.*[9] used SVM for exploiting the range and intensity information of human faces for ethnicity and gender identification. Simple techniques have also been used for gender recognition. Yang *et al.*[10] improved gender classification using texture normalization. Gaussian Process Classifier was used by Kim *et al.*[11] in their proposed system for gender recognition.

Several weak classifiers were combined by Baluja and Rowley[12] for pixel value comparisons on low resolution gray scale images in their AdaBoost based gender classifier. They used normalized images of size 20×20 in their experiments performed on FERET database, which showed an overall recognition rate of 90%. Lu and Shi[13] employed the fusion of left eye, upper face region and nose in their gender classification approach. Their results showed that the fusion of facial regions approach outperformed the whole face approach. Extending this idea, Alexandre[14] used a fusion approach based on features from multiple scales. They worked on normalized images of resolutions (20×20, 36×36 and 128×128) to extract shape and texture features. For texture features, they used Local Binary Pattern[15] approach.

Zheng and Lu[25] gave a comparison of 6 types of features using three classifiers and showed that for FERET database the best accuracy (99.1%) was obtained with features based on local Gabor binary pattern and LAD (LGBP-LDA) and SVM with automatic confidence (SVMAC).

Grosso *et al.*[31] addressed the problem of identifying the factors that critically affect the accuracy of the methods for face identification and gender categorization. According to their findings, gender classification can be made independent from appearance-based factors like facial expression, illumination condition and skin color. Caifeng[30] employed multiscale LBP as a feature descriptor, Adaboost to select the discriminative LBP features and SVM for classification, and obtained the performance of 94.81% on the Labeled Faces in the Wild (LFW) database. The reported accuracy is on facial images taken in an uncontrolled environment. The performance of this method is not given on facial images taken in controlled environment.

3. Dyadic Wavelet Transform

We used Dyadic Wavelet Transform (DyWT) together with SLBP for face description. Unlike DWT, it is translation invariant and can capture the micro-patterns like edges in a better way. In the following paragraphs, we give an over view of DyWT. Complete detail can be found in Ref. 16.

DyWT involves two types of bases functions: scaling and wavelet functions. A scaling function $\phi(t)$ satisfies the following two-scale relation:

$$\phi(t) = \sum_k h[k]\sqrt{2}\phi(2t-k). \tag{3.1}$$

Its Fourier Transform (FT) satisfies the following relation:

$$\hat{\phi}(w) = \frac{1}{\sqrt{2}}\hat{h}\left(\frac{w}{2}\right)\hat{\phi}\left(\frac{w}{2}\right). \tag{3.2}$$

Using the scaling function $\phi(t)$, define a function $\psi(t)$ with the following relation:

$$\psi(t) = \sum_k g[k]\sqrt{2}\phi(2t-k).$$

Its Fourier transform is given by

$$\hat{\psi}(t) = \frac{1}{\sqrt{2}}\hat{g}\left(\frac{w}{2}\right)\hat{\phi}\left(\frac{w}{2}\right). \tag{3.3}$$

The function $\psi(t)$ is called dyadic wavelet transform if for $A > 0$ and B, some it satisfies the following inequality:

$$A \leq \sum_{-\infty}^{+\infty}\left|\hat{\psi}(2^{jw})\right|^2 \leq B.$$

Projection of any L^2 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 $\tilde{\phi}(t)$ is defined by the following two-scale relation:

$$\tilde{\phi}(t) = \sum_k \tilde{h}[k]\sqrt{2}\tilde{\phi}(2t-k),$$

and the dual wavelet function $\tilde{\psi}(t)$ satisfies the following two scale relation:

$$\tilde{\psi}(t) = \sum_k \tilde{g}[k]\sqrt{2}\tilde{\phi}(2t-k).$$

The Discrete Fourier Transform (DFT) of the filters $h[k], g[k], \tilde{h}[k]$, and $\tilde{g}[k]$ is denoted by $\hat{h}(w), \hat{g}(w), \hat{\tilde{h}}(w), and\ \hat{\tilde{g}}(w)$ respectively. These filters are dyadic wavelet filters if the following condition is satisfied:

$$\hat{\tilde{h}}(w)\hat{h}^*(w) + \hat{\tilde{g}}(w)\hat{g}^*(w) = 2, \quad w \in [-\pi, +\pi]. \tag{3.4}$$

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

Theorem 1. (*á trous Algorithm*) the reconstruction condition (3.4) is used to obtain the following decomposition formulae

$$a_{j+1}[n] = \sum_k h[k]a_j[n+2^j k], \quad j = 0,1,\ldots, \tag{3.5}$$

$$d_{j+1}[n] = \sum_k g[k]a_j[n+2^j k], \quad j = 0,1,\ldots, \tag{3.6}$$

where $a_0[n]$ is given by $a_0[n] = \int_{-\infty}^{+\infty} f(t)\emptyset(t-n)dt$, and the following reconstruction formula

$$a_j[n] = \frac{1}{2}\sum_k (\tilde{h}[k]a_{j+1}[n-2^j k] + \tilde{g}[k]d_{j+1}[n-2^j k]), \quad j = 0,1,\ldots. \tag{3.7}$$

Equations (3.5) and (3.6) define the Fast Dyadic Wavelet Transform (FDyWT) and are used for projection of a 1D function onto the space of dyadic wavelets. In case of 2D function i.e. images, the projection is obtained by applying FDyWT first in x-axis (horizontal) and then in y-axis (vertical) direction. Equation (3.7) defines the Inverse Dyadic Wavelet Transform (IDyWT).

A family of spline dyadic wavelets is defined with wavelet filters $h[k]$ and $g[k]$ whose Fourier Transforms are given by:

$$\hat{h}(w) = \sqrt{2}\, e^{-i\varepsilon/2}\left(\cos\frac{\omega}{2}\right)^{m+1} \tag{3.8}$$

$$\hat{g}(w) = (-i)^s \sqrt{2}\, e^{-\left(i-\frac{s}{2}\right)}\left(\sin\frac{\omega}{2}\right)^r \tag{3.9}$$

where $m \geq 0$ denotes the degree of the box-spline and

$$\varepsilon = \begin{cases} 1 & \text{if } m \text{ is even} \\ 0 & \text{if } m \text{ is odd} \end{cases}$$

and

$$s = \begin{cases} 1 & \text{if } r \text{ is odd} \\ 0 & \text{if } r \text{ is even} \end{cases}$$

The degree r is independent of m. Different values of r and m define a family of spline dyadic wavelets. In this paper, we explore this family for face representation to be used in gender recognition.

4. Spatial Local Binary Pattern (SLBP)

LBP descriptor computed using LBP operator introduced by Ojala *et al.*[17] is one of the widely used texture descriptors that have shown promising results in many applications.[15,18–21] Ahonen *et al.*[22] used it for face recognition, Lian and Lu[13] and Sun *et al.*[23] 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 3×3-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.[15]

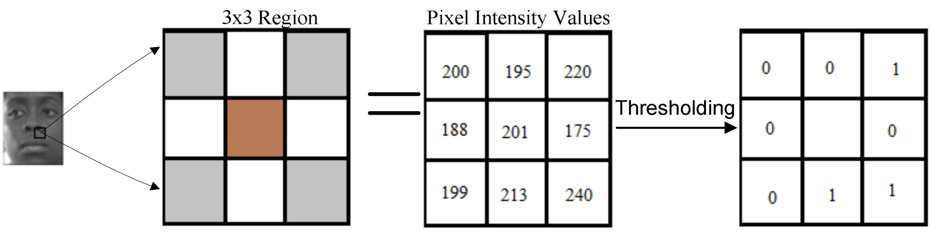

Fig. 1. LBP operator.

The general LBP operator is denoted by $\mathrm{LBP}_{\mathrm{P,R}}$ and is defined as follows:

$$\mathrm{LBP}_{\mathrm{P,R}} = \sum_{i=1}^{P} 2^i S(p_i - p_c) \tag{4.1}$$

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

$$S(p_i - p_c) = \begin{cases} 1, & p_i - p_c \geq 0 \\ 0, & p_i - p_c < 0. \end{cases} \tag{4.2}$$

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 $f_l(x, y)$ is defined as:

$$H(i) = \sum_{x,y} I\{f_l(x, y) = i\}, \quad i = 0, \ldots, n-1 \tag{4.3}$$

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

$$I\{x\} = \begin{cases} 1, & x \text{ is true} \\ 0, & x \text{ is false.} \end{cases} \tag{4.4}$$

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.

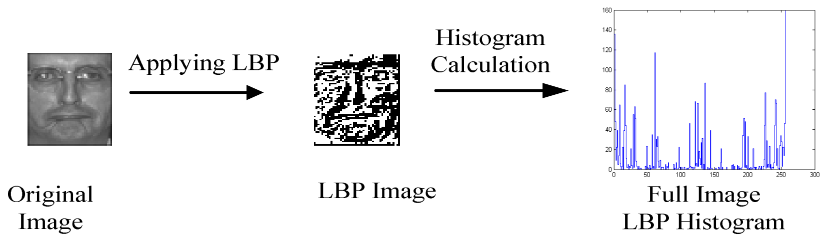

Fig. 2. LBP histogram for a facial image.

To overcome this issue, spatially-enhanced LBP histogram is calculated. Figure 3 shows the process of computing spatially enhanced LBP histogram. An image is divided into non-overlapping blocks; LBP histogram is calculated from each block and all histograms are concatenated.

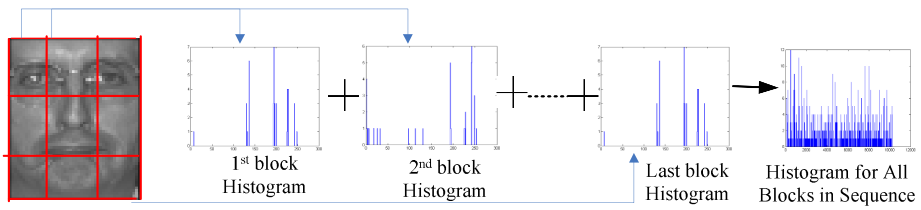

Fig. 3. Spatially-enhanced LBP histogram for a facial image.

Basic 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 view of our experience, in this paper we explored uniform version of LBP with P and R as 8 and 1, respectively.

5. Gender Recognition

The proposed system for gender recognition follows the general architecture of a recognition system i.e. it consists of four main steps: 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 a feature subset selection method to increase the recognition accuracy and to reduce the time complexity. For classification we used minimum distance classifier and explored its effect with City-block distance (L1), Euclidean Distance (L2), and Chi-square distance (CS) distance.

The block diagram of the recognition system which we used for gender recognition is shown in Figure 4. In the following subsections, we give the detail of the techniques used for different stages of the recognition system.

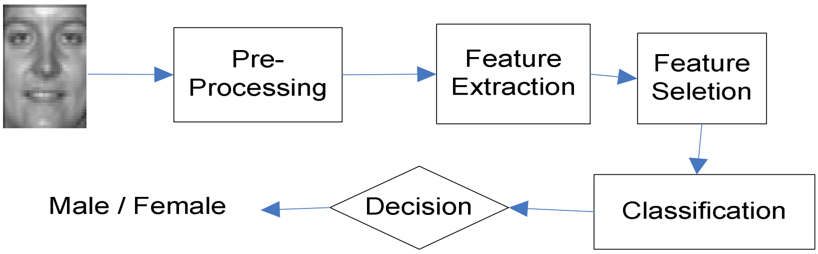

Fig. 4. Gender recognition system.

5.1. *Preprocessing*

The facial images are normalized i.e. all images are resized to the same size, and eye locations and tip of nose in each image are mapped to the same locations.

5.2. *Feature extraction*

For DyWT-LBP descriptor, we used SLBP and DyWT. DyWT decomposes an image in to a number of sub-bands at different scales. At each scale there are three high-frequency sub-bands LH, HL and HH and one low frequency sub-band LL. At every decomposition level LL is further decomposed into low-frequency and high-frequency sub-bands. Each high-frequency sub-band captures the texture micro-patterns at that particular scale along one of the three directions (horizontal, vertical and diagonal) and low-frequency sub-band captures the overall structure of different objects present in an image. Figure 5 shows an image which is decomposed using DyWT up to scale 2. SLBP extracts texture micro-structures. After decomposing an image using DyWT, SLBP operator is applied on each sub-band for extracting texture micro-structures at various scales and orientations.

Specifically the following steps are employed for DyWT-LBP descriptor of each facial image:

Step 1: Decompose an image using DyWT up to scale N.
Step 2: Apply SLBP on each sub-band.
Step 3: Concatenate SLBP histograms obtained from each sub-band.

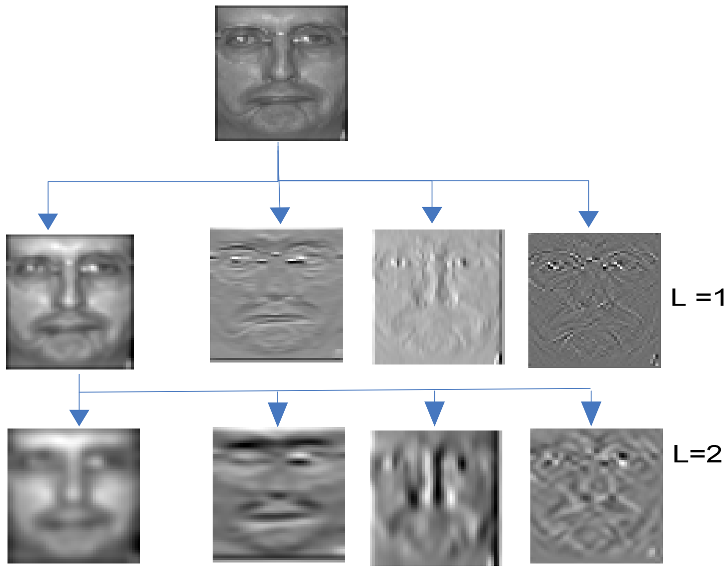

Fig. 5. Example of image from FERET database in to sub-bands.

Step 4: To reduce the dimension of the feature space and to remove the redundant features, apply Sun's FSS (see Section 5.2) technique using a wrapper approach for feature subset selection.

These steps have been shown in Figure 6.

When using DyWT for decomposition, the important question is how many scales and which wavelet filters result in the best performance for gender recognition. The spline dyadic wavelet filters given by Equations (3.8) and (3.9) involve two parameters m and r. Different values of these parameters generate different spline dyadic wavelets which have different impact on the recognition accuracy. SLBP also involves many parameters: neighborhood (P, R), mapping, and block sizes. A random choice of these parameters does not give best result. It is essential to explore the space of these parameters for optimal set of parameters.

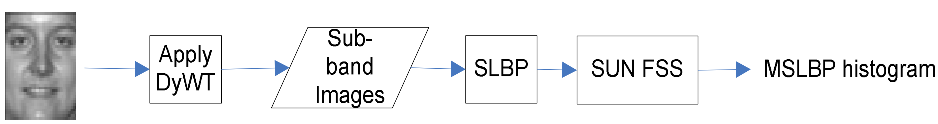

Fig. 6. System diagram of the proposed method.

5.3. *Feature subset selection*

DyWT-LBP descriptor involves a huge number of redundant features. These features not only increase the time complexity but also decrease the recognition rate. To reduce the dimension of the feature space, we employed feature subset selection (FSS) algorithm proposed by Sun *et al.*,[20] which is reported to be the best for two-class problems, please note that gender recognition is a two-class problem. This algorithm is simple, powerful and robust; it involves two free parameters: kernel width σ and regularization parameter λ. Though the authors claim that the efficiency of the algorithm is not dependent on a particular choice of these parameters, our experience is that the number of selected features and the recognition performance do depend on a particular choice of the values of these parameters. Finding the proper values of these parameters is imperative for optimal recognition rate. Sun's method is a filter method; however we employed it as a wrapper method in our system to have better performance. We perform grid search as described below in order to achieve optimal values of the parameters.

Algorithm 1

```
For σ = 0.1:0.2:2
    For  λ = 0.1:0.2:2
        SelectedF = SelectFeatures_SunMethod (σ, λ);
        acc = Classify_ with_ NN (SelectedF);
        Compare previous accuracy with acc and update;
    End
End
```

Different values of σ and λ result in the selection of different numbers of features, which yield different recognition rate.

5.4. *Classification*

For validating the usefulness and the potential of DyWT-LBP descriptor based on DyWT, SLBP and FSS, we employed minimum distance classifier to keep the system complexity simple. Many metrics are possible for minimum distance classifier and its performance depends on the proper choice of a metric. A metric that is tuned to the structure of the feature descriptor under-consideration very well results in optimal recognition accuracy. We examined three metrics: City block distance (L1), Euclidean distance (L2), and Chi-square (CS).

6. Experiments and Discussion

In this section, we present and discuss the results of the proposed gender recognition system. We tested the system using two well-known public domain facial databases: FERET[6] and Multi-PIE.[24] First, we give an overview of these databases and the experimental setup used for each database.

6.1. *FERET*

It is one of the challenging database for face recognition. The database contains frontal, left or right profile images with some variations in pose, expression and lightning. It consists of different sets; for our experiments we used two sets fa and fb. We normalized and cropped each image contained in each set to the size 60×48 pixels. In sets fa and fb, there are total 2400 images of 403 male subjects and 403 female subjects. Out of 1486 images of males, we used 746 images for training and 740 images for testing. Similarly out of 914 female facial images, 458 images were used for training and the remaining 456 images were used for testing. Some sample facial images taken from FERET database have been shown in Figure 7.

Fig. 7. Sample normalized male and female images from FERET database.

6.2. *Multi-PIE*

Multi Pose Illumination and Expression (Multi-PIE) database was collected at CMU between October 2004 and March 2005 for validation of face recognition system across pose and illumination. It contains 755,370 images of 337 male and female subjects. Individual session attendance varied between a minimum of 203 and a maximum of 249 subjects. For our experiments, we selected a total of 1990 images of 199 subjects (102 male and 97 female) with variation of pose, illumination and expressions. We normalized each image to the size 60×60 pixel. Some sample normalized images of males and females have been shown in Figure 8. Training set contains 1046 images (544 male and 502 female), whereas testing set contains 944 images (476 male and 468 females).

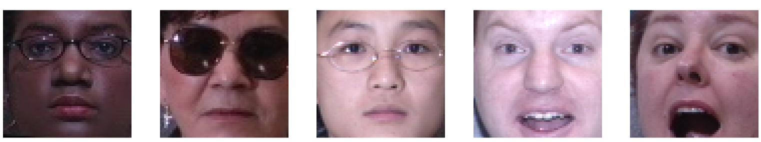

Fig. 8. Sample normalized male and female images from Multi-PIE database.

6.3. *Parameter settings*

DyWT-LBP descriptor involves many parameters: m and r parameters for spline dyadic wavelets for DyWT, number of levels in DyWT decomposition, type of LBP (simple, uniform and rotation invariant), type of LBP histogram (normalized and simple), neighborhood (P, R) for LBP and block size for SLBP. We performed experiments with different combinations of these parameters.

For our experiments, we used uniform LBP with neighborhood (8, 1) i.e. neighborhood with 8 points and radius 1. Furthermore, we examined two types of histograms: normalized and simple. We found that simple histogram performs better than its normalized version.

We tried three distance measures for minimum distance classifier: L1, L2, and CS. L1 achieved the best results. CS gave the comparable results but its time complexity is very high. The performance of L2 is very poor. In our experiments discussed below, we used L1.

6.3.1. *Effect of block sizes*

For SLBP, we tested a number of block sizes and we report the results with block sizes that gave the best three recognition rates. In case of FERET database, the block sizes which gave the best results are: 15×2, 12×12, and 10×12 pixels; for Multi-PIE database, the best results were given by the block sizes: 6×12, 8×8, 16×16. The effect of block sizes on the recognition rate for the two databases is shown in Figure 9. First two bars (in green) show the recognition accuracy of two best block sizes for LBP. The next three bars (in orange) show the best three recognition rates obtained with three block sizes: 15×12, 12×12, and 10×12 pixels on FERET database. The last three bars (in blue) show the best recognition results obtained with block sizes: 6×12, 8×8, 16×16 on Multi-PIE database. From Figure 9, it is obvious that smaller block sizes give better results in case of both databases; for FERET database block size 10×2 gives the best result (**98.66%**) whereas the best result (**98.64%**) is obtained by block size 8×8 for Multi-PIE database. In Ref. 13 LBP with uniform mapping and block size of 16×16 and 32×32 is used which resulted in an accuracy of 93.46% as shown by the first green bar in Figure 10. It clearly shows that our system outperforms with an increase of 5.20% as compared to the system proposed in Ref. 13.

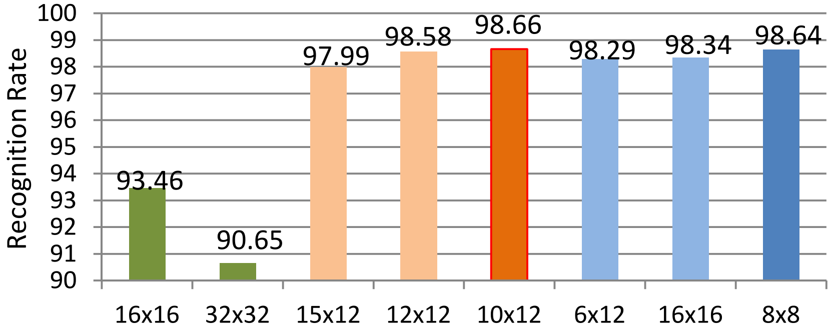

Fig. 9. (Color online) Effect of block sizes. First two bars (1–2) show the recognition rate with basic LBP.[13] Next three bars (3–5) give the recognition accuracy with SLBP on FERET database. Last three bars (6–8) represent the recognition accuracy with SLBP on Multi-PIE database.

6.3.2. *Effect of spline dyadic wavelets*

Different values of parameters r and m define different types of spline dyadic wavelets. We examined the effect of spline dyadic wavelets for $r = 1, 2$ and $m = 1, 2, 3, 4$. Figure 10 shows the effect of these parameters; in this figure we report the best results obtained with individual sub-bands and different combinations of sub-bands across scales. It is obvious that the overall best result (**96.74%**) was given by high frequency sub-band (LH) at scale 3. The spline dyadic wavelet transform with parameter values $r = 1$ and $m = 1$ and the L1 minimum distance classifier gave this best result. Please note that these results are with only DyWT (without using LBP) and FERET database. In onward experiments, we used spline dyadic wavelets with $r = 1$ and $m = 1$.

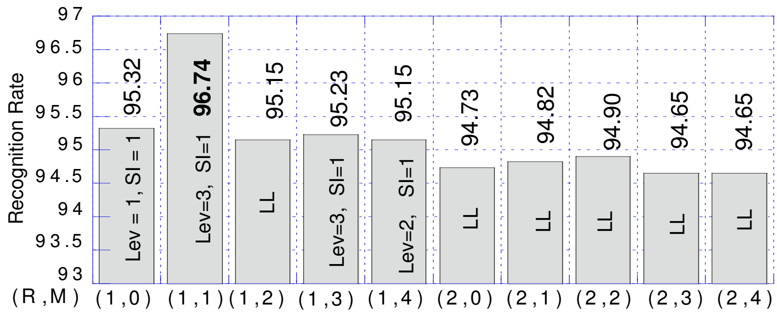

Fig. 10. Effect of different spline dyadic wavelets and scales. Here "Lev" means levels (scales) of decomposition and "S" means the sub-band, S1 means LH sub-band.

6.3.3. *Effect of decomposition levels*

We tested 5 DyWT decompositions with 1, 2, 3, 4, and 5 levels. For each decomposition, we computed SLBP from each sub-band and fused the decision of minimum distance classifier for each subband using addition. Table 1 shows the effect of decomposition levels; the decomposition with 2 levels gave the best recognition accuracy.

Table 1. The effect of DyWT decompositions on the recognition rate.

Decomp. Levels	L1			CS		
	Male	Female	Overall	Male	Female	Overall
1	99.05	98.24	98.75	98.78	98.02	98.49
2	**99.19**	**98.68**	**99.00**	99.05	98.68	98.91
3	98.24	98.46	98.33	97.57	98.25	97.83
4	97.83	97.15	97.58	97.97	96.93	97.58
5	97.02	96.05	96.66	96.89	96.05	96.57

6.3.4. *Effect of DyWT-LBP descriptor*

Using uniform LBP with simple histogram for SLBP, the best result on FERET database obtained in our experiments with block size of 10×12 and L1 minimum distance classifier is **98.66%.** However when we applied SLBP on DyWT decomposed image, DyWT-LBP resulted in **99.00**% accuracy as shown in Figure 11, there is a small improvement in the recognition accuracy. Using the same parameter settings for SLBP

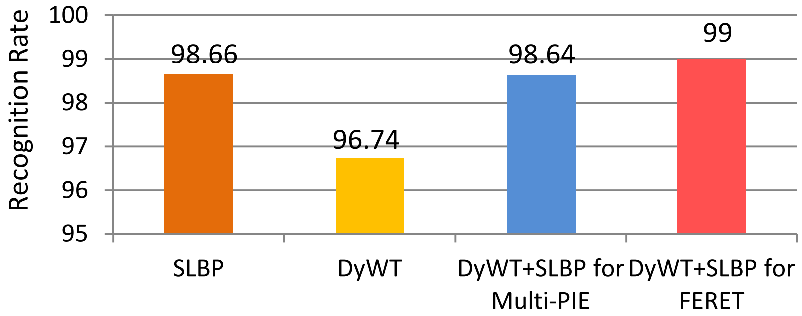

Fig. 11. (Color online) Best result with only SLBP (first bar) and only DyWT (second bar) on FERET database. Best recognition rate with MSLBP on FERET (third bar) and Multi-PIE (forth bar) databases.

and DyWT, DyWT-LBP gave the best results of **98.64%** on Multi-PIE database with block size of 8×8 and L1 minimum distance classifier; in this case there is no improvement in the recognition rate as compared to SLBP.

6.3.5. *Effect of feature subset selection*

It is noted in our experiments that smaller block sizes gave the best accuracy. The smaller block sizes not only increase the recognition rate but also increase the computational complexity of the system by increasing the number of features. To overcome the problem of the curse of dimensionality, we employed Sun's algorithm for reducing the dimension of the feature space. In our case, it not only reduced the number of features but also increased accuracy. This algorithm involves two parameters: σ and λ, the recognition accuracy depends on the values of these parameters, see Table 2. For finding the optimal

Table 2. The effect of the parameters σ and λ on FSS by Sun's algorithm for Multi-PIE.

σ	λ	# Selected Features	L1	CS
0.7	1.3	494	98.48	98.29
0.7	1.5	420	98.38	98.44
0.7	1.7	407	98.49	98.35
0.7	1.9	340	98.44	98.24
0.9	0.1	2556	98.69	98.45
0.9	0.3	1382	98.53	98.44
0.9	0.5	1050	98.69	98.64
0.9	0.7	627	**99.09**	98.59
0.9	0.9	659	98.74	98.75
0.9	1.1	546	98.28	98.09
0.9	1.3	470	98.38	98.64
0.9	1.5	393	98.43	98.19
0.9	1.7	314	98.28	98.09
0.9	1.9	268	98.39	98.39

values of these parameters, we performed search on the grid $[0.1\ 2] \times [0.1\ 20]$ with an increment of 0.2 for each parameter. After extracting features using the best parameter setting for SLBP and DyWT, which resulted in an accuracy of 99% for FERET database, we applied Sun's algorithm that not reduced the features by 67% but also increased the accuracy from 99% to 99.25%. This result was obtained with σ and λ values of 1.3 and 0.7, respectively. Similarly in case of Multi-PIE, Sun's algorithm with σ and λ values of 0.9 and 0.7, respectively, not only reduced features from 3227 to 627 but also increased accuracy from 98.64 to 99.09% as shown in Figure 12.

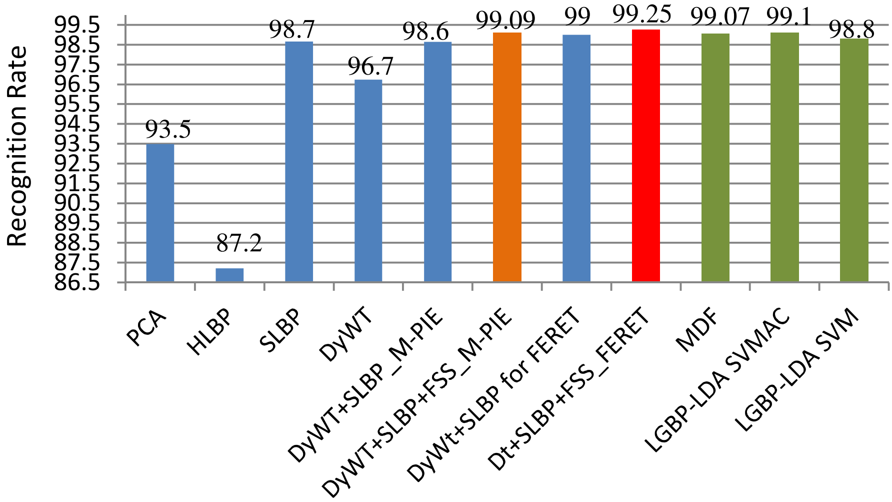

Fig. 12. (Color online) Comparison of the proposed system with stat of the art gender recognition systems.

6.4. *Comparison with existing methods*

For validating the performance of our gender recognition system in contrast with published systems, we compare it with stat of the art gender recognition systems such as based on Local Gabor Binary Pattern with LDA and SVMAC (LGBP-LDA SVMAC),[25] Local Gabor Binary Pattern with LDA and SVM (LGBP-LDA SVM),[25] and Multi-resolution Decision Fusion (MDF).[14] These three systems have been reported to achieve the best recognition results so far in the literature. The recognition accuracies of these systems have been shown in the last three bars (in green) of Figure 10. It is obvious that our proposed system gives promising results, which are comparable with those of the stat of the art gender recognition systems. The blend of SLBP and DyWT gives rise to a feature descriptor that overcomes the drawbacks of holistic LBP (HLBP) and performs extremely better than HLBP and PCA whose results are shown in the first two bars of Figure 10. The reason why the proposed recognition system performs better than the stat of the art methods is that the DyWT-SLBP feature descriptor encodes local texture micro-structures, which play a key role in the discrimination of objects, at various scales, and the locally learning based FSS algorithm eliminates the redundant features thereby increasing the recognition rate.

7. Conclusion

We proposed a new DyWT-LBP descriptor for gender recognition using DyWT and LBP. The dimension of the feature space generated by DyWT-LBP becomes excessively high; to deal with this problem we employed Sun's FSS algorithm that not only reduced the dimension of the feature space but also improved the recognition accuracy. We found that L1 minimum distance classifier gave the best result with the proposed DyWT-LBP descriptor. We validated the performance of the proposed gender recognition system on two public domain databases: FERET and Multi-PIE, which include facial image with variation of pose and illumination. DyWT-LBP descriptor with $r = 1$, $m = 1$, 2 levels for DyWT decomposition, block size of 10×12 pixels, uniform LBP with simple histogram for SLBP gave the best result (99%) on FERET database, which was further improved by Sun's algorithm to 99.25%. The same parameter settings for DyWT-SLBP but with block size 8x8 resulted in the best performance (98.64%) on Multi-PIE database, that was further enhanced to 99.09% by Sun's algorithm. Comparison with the stat of the art gender recognition systems showed that the proposed system it outperformed in recognition accuracy. The proposed system can produce good results even in the presence of variation in pose, illumination and expression. In our future work we will explore DyWT and SLBP with sophisticated classifiers like SVM and will test it on other facial databases.

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