Low Resolution Sparse Binary Face Patterns

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Abstract: Automated recognition of low resolution face images from thumbnails represent a challenging image recognition problem. We propose the sequential fusion of wavelet transform computation, local binary pattern and sparse coding of images to accurately extract facial features from thumbnail images. A minimum distance classifier with Shepard's similarity measure is used as the classifier. The proposed method shows robust recognition performance when tested on face datasets (Yale B, AR and PUT) when compared against benchmark techniques for very low resolution (i.e. less than 45x45 pixels) face image recognition. The possible applications of the proposed thumbnail recognition include contextual search, intelligent image/video sorting and groups, and face image clustering.

1 INTRODUCTION

The need to have biometric features in electronic devices having personalised contents is seen to grow in the upcoming years. Among several biometric modalities face images represent an obvious method to reveal identity of the individual. This paper focuses on recognition of faces from thumbnails that has several applications in mobile devices such as contextual searching, personalisation of contents, and as a modality for biometric security, while in surveillance systems they reflect as very low resolution (VLR) problem (Zou and Yuen, 2010).

The automated recognition of faces in general is a challenging task for low resolution digital face images taken under unconstrained recognition environments (Li et al., 2010; Lai and Jiang, 2012; Marciniak et al., 2012). The natural variability that complicates the face recognition methods include changes in face poses, illumination changes, occlusions, aging, camera sensing errors, and changes in facial expressions. As a solution to this real world problem, several techniques were proposed by researchers. Most of these existing solution made use of the technique of super resolution to generate a high resolution image from the available low resolution image. Earlier methods used simple interpolation techniques for generating the higher resolution images. Because of its unsuitability in producing acceptable results, several super resolution algorithms involving complex optimization problems were proposed (Baker and Kanade, 2000), (Freeman et al., 2000), (Xu et al., 2014). These methods suffered from the problem of computational complexity thereby making these unusable in real time conditions.

In this paper, we focus on recognising faces from very low resolution images under the influence of different natural variability tested on various standard face datasets. We use a combination of feature formation techniques that partly mimic the response of vision systems in human brain and encode the features to reduce the impact of natural variability.

2 SPARSE BINARY PATTERNS

The proposed method inspires from the psychovisual similarity in the functioning of the neurons in the layer V1 of the visual cortex with that of wavelets (Field, 1999), sparse features and Shepard's perception measure for distance calculations. The proposed feature extraction technique from thumbnail images are summarised as a block diagram in Fig. 1 and the summary of the method is provided in Algorithm 1. The algorithm primarily consists of wavelet computation, local binary pattern based image description and a sparse distributed feature extraction scheme. The wavelet transform of the facial image allows one to

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capture the shape features of the image after neglecting irrelevant noisy edge features. The local binary pattern enables the efficient description of local facial features in a pixel level. The sparse distributed feature extraction method converts the local features present in the local binary pattern image into a global feature descriptor.

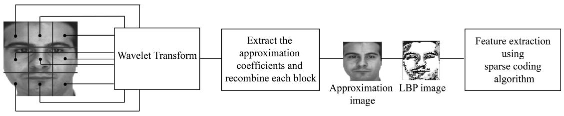


Figure 1: The block diagram of the proposed feature extraction technique.

The proposed feature extraction technique divides the input image into non-overlapping blocks and performs a block-wise computation of wavelet transform. The two dimensional discrete wavelet transform is given by Eq 1.

$$d_{j,n}^{k} = \int_{-\infty}^{\infty} 2^{j}\psi^{k}(2^{j}x_1 - n_1, 2^{j}x_2 - n_2)s(x); \qquad (1)$$

where, $k = \{0,1,2,3\}$, $s(x)$ is the input image and ψ^k is the mother wavelet is defined by: $\psi^0(x_1,x_2) = \phi(x_1)\phi(x_2)$, $\psi^1(x_1,x_2) = \phi(x_1)\psi(x_2)$, $\psi^2(x_1,x_2) = \psi(x_1)\phi(x_2)$, and $\psi^3(x_1,x_2) = \psi(x_1)\psi(x_2)$. The two dimensional wavelet transform results in four sub-bands consisting of wavelet coefficients. The first sub-band contains the low frequency coarse features of the image while the other three sub-bands contain the high pass detail coefficients that give information about horizontal, vertical and diagonal edges present in the image. We make use of the low frequency or approximation coefficients since it contains the shape features of the image (Zhang et al., 2004) and the detail coefficients are neglected for further processing.

The proposed feature extraction technique begins by dividing the input image into non-overlapping blocks followed by the wavelet computation of each image block. From the wavelet sub-bands of each block, the approximation image of each block is extracted and combined to obtain the approximation image of the input image. The block-wise wavelet transform allows to capture more local features compared to applying the wavelet transform to the whole of the image. As mentioned above, a careful selection of wavelet base is required to improve the performance of the system. But no study has been previously conducted regarding the suitability of each family of wavelet bases in various image processing applications. So, we have to experimentally validate the performance of each wavelet base for the given low resolution face recognition problem.

Algorithm 1: Feature extraction using sparse distributed representation for face recognition.

Input: Low resolution facial image(I) of dimension $m \times n$
Output: Feature vector subset (F^*) of length $C = (k \times m \times n)/(W \times 2)$

```
Divide the image into blocks of size M×N to get L number of blocks
for l=1 to L do
    Compute wavelet transform
    Extract the approximation coefficients
end for
Combine the approximation image blocks to get the approximation image(I_A) of input image(I)
for Each pixel I_A(x,y) in I_A do
    Extract the 8 immediate neighbours of I_A(x,y)
    Threshold each neighbour using I_A(x,y) as the threshold
    I_B(x − i, y − j) = { 1,  I_A(x−i, y−j) ≤ I_A(x,y)
                        { 0,  otherwise
    i, j ∈ {−1, 1}
    The LBP value of I_A(x,y) is obtained as
    I_LBP(x,y) = I_B(x−1,y−1) + 2I_B(x−1,y) + 4I_B(x−1,y+1) + 8I_B(x,y+1) + 16I_B(x+1,y+1) + 32I_B(x+1,y) + 64I_B(x+1,y−1) + 128I_B(x,y−1)
end for
Convert the image I_LBP to P bit planes
for p=0 to P−1 do
    Select p^th bit plane
    for c=1 to C do
        Choose W number of binary pixels b* from I_LBP randomly
        B(c) = Σ_{l=1}^{W} b*_l
    end for
    Divide the feature vector B_p into groups of X number of B* feature cells
    B_p = [{B_p(1), B_p(2)..B_p(C/X)}, ..., {B_p(C − C/X), B_p(C−1)..B_p(C)}]
    for every element in a group in B_p do
        F*_p(c) = { 1,  B*(c) = max(B*)
                  { 0,  otherwise
    end for
end for
for c=1 to C do
    F*(c) = Σ_{p=1}^{P} 2^{p−1} F*_p(c)
end for
```

Spatial change detection is the next stage in our algorithm, that makes use of local binary pattern (LBP) image (Ojala et al., 2002; Ahonen et al., 2006) of the resulting wavelet approximation image. LBP features introduce illumination invariance that is useful to improve the feature quality of faces. The LBP image is computed from the approximation image of the wavelet decomposition stage by considering a neighbourhood around each pixel value followed by thresholding these neighbouring values with the central pixel as threshold and combining the resulting binary vector to obtain a decimal value. Even though, many types of neighbourhood selections are possible such as rectangular neighbourhood, and circular neighbourhood of various sizes, we use the 3×3 square neighbourhood owing to its simplicity. Further, the uniform LBP is used for simplicity in implementation[1].

After computing the LBP image, we have to generate a feature vector that can represent the facial features efficiently and robustly. In the traditional local binary pattern based face recognition approaches, the feature vector is represented as a histogram. This is done by first dividing the LBP image into several overlapping or non-overlapping blocks and then computing the histogram of each block and finally concatenating all the histograms. Instead of the conventional method of using histograms for feature description, we propose to use the feature extraction technique mentioned in (Sudhakaran and James, 2015). This method is inspired by the sparse processing capability of human brain. In this method, the LBP image is first converted to bit planes, then the binary feature vectors are extracted from each bit plane by performing the random selection, aggregation and binarization operation using winner take all networks as explained in (Sudhakaran and James, 2015). Here, we do not make use of the gradient images instead use the LBP images. After that, the binary feature vectors are combined together to obtain the final facial feature vector. The selection of various parameters required for reproducing the result is explained in the Experiments section.

Once the feature descriptors of a face image is computed, the next step is to apply it to a suitable classifier. Here, we use the simple yet very effective nearest neighbour classifier (Cover and Hart, 1967). In this, the distance between the test image feature vector and the feature vectors of all the train images are computed and then the pair with the minimum distance is found. The test image is then assigned the label of the train image obtained. The advantage of the nearest neighbour classification is its simplicity. We modify the conventional nearest neighbour metrics by using the Shepard's similarity measure (Shepard, 1987) as it has interesting properties related to perception of similarity; and is a normalising function to reduce the inter-feature distance outliers. Let $f_{train}(i)$ be the train feature vector and $f_{test}(i)$ be the test feature vector, each of length N. $i = 1, 2, \ldots N$. Then, the Shepard's similarity measure is computed as:

$$d = \sum_{i=1}^{N} e^{-|f_{train}(i) - f_{test}(i)|} \tag{2}$$

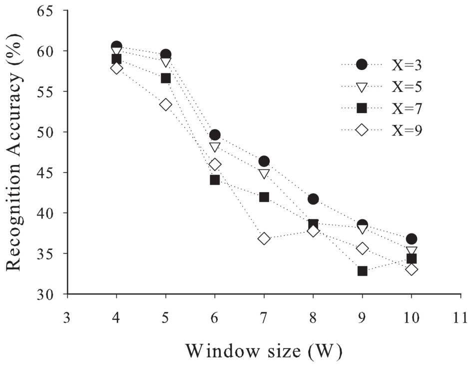
Since Eq. 2 is a similarity measure, instead of finding the pair with the minimum distance, here we will find the pair with the maximum similarity value.

3 EXPERIMENTS AND RESULTS

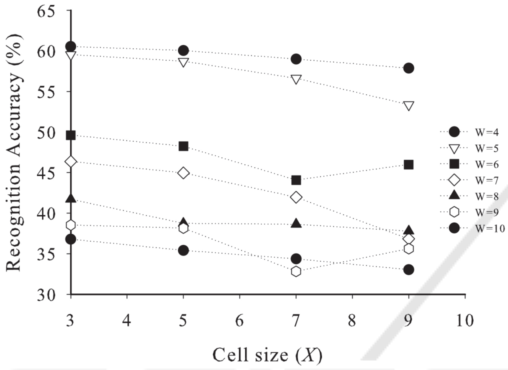
The performance of the proposed method was evaluated by comparing the recognition accuracy with principal component analysis (PCA) (Turk and Pentland, 1991), kernel PCA (KPCA) (Kim et al., 2002), kernel Fischer analysis (KFA) (Liu et al., 2002), Gabor PCA (GPCA), Gabor KPCA (GKPCA), and Gabor KFA (GKFA). Since no standard face databases with low resolution images are available, the AR face database (Martinez, 1998), extended Yale face database B (Lee et al., 2005) and the PUT face database(Kasinski et al., 2008) were selected for the performance evaluation. All the images in the databases were smoothed and downsampled to produce the low resolution images. Previous low resolution face recognition literatures also adapted similar technique for analysing the results (Li et al., 2010; Patel et al., 2014).

The first experiment conducted was to determine the various parameters that will give the best performance. It was done on the AR face database with the size of the images downscaled to 40×30. The parameters required for the feature extraction stage are the window size (W), cell size (X) and the degree of overlap (k). From the different experiments explained in (Sudhakaran and James, 2015), the value of k can be fixed as 2 since the accuracy is not much varied with the value of k. The remaining two parameters, W and X are selected by analysing the performance of the proposed method for various values. Here, the wavelet approximation image selection step is omitted since the selection of a wavelet base is pending. The local binary pattern of image is computed and then feature extraction is done by varying the parameters and the recognition accuracy for different values

[1] Uniform local binary patterns are binary vectors that contains at most 2 changes in its elements (change from 0 to 1 or vice versa). The reason for selecting the uniform LBP is from the fact that previous studies have shown that they tend to occur more in images compared to non uniform patterns(Pietikäinen, 2010).



(a)



(b)

Figure 2: The recognition accuracy obtained for different values of *window size (W)* and *cell size (X)*. Fig. 2(a) shows the plot of recognition accuracy versus window size for different values of *cell size (X)*. Fig. 2(b) depicts the graph of accuracy against cell size for different values of *window size (W)*.

of W and X are calculated. The result obtained is illustrated in Fig. 2. The figure shows that, the recognition accuracy decreases as the window size is increasing. But the accuracy is more or less same for the window sizes W= 4 and 5. Since the feature vector size increases with reduction in window size, the window size is chosen as W=5. The cell size is selected as 3. The window size for the wavelet operation is selected as 5×5. These values of W and X are then used in all the experiments mentioned in this paper.

In order to select the suitable wavelet base, the recognition accuracy of AR face database for different wavelet bases were computed. The size of all images was downsampled to 40×30. The following families of wavelet functions were used in the experiment: Haar, Daubechies (db1), biorthogonal (Mallat, 1999) (*bior1.1*) and reverse biorthogonal (Gao and Yan, 2010) (*rbio1.1, rbio2.2, rbio2.4, rbio2.6, rbio2.8, rbio3.1, rbio3.3, rbio3.5, rbio3.7, rbio3.9*). The result obtained is shown in Fig. 3. From the graph, we can see that the best result was obtained

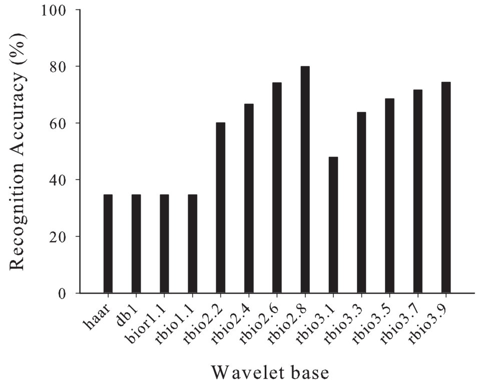


Figure 3: The recognition accuracy obtained when different families of wavelet bases were used.

by the reverse biorthogonal wavelet family, especially the *rbio2.8* wavelet. The reverse biorthogonal wavelet was used for evaluating the performance of the algorithm.

After finding the optimal parameters, the performance of the proposed low resolution face recognition system is tested on the different face datasets mentioned above. The results obtained are explained below. To check the resilience of the proposed method against illumination changes, the Yale face database B was used since it contains face images captured with varying illumination settings. The set is subdivided into 5 subsets based on the location of the illumination source. Experiments were conducted on each of the subset separately. From each image in the dataset, the face region was cropped and resized to 45×45 for conducting the experiment. The first image in each of the subset was selected as the training image and the remaining images were selected for testing. The recognition accuracy was then computed as a ratio of the number of correctly identified samples to the total number of samples tested. The recognition accuracy for the proposed method as well as the other methods compared is given in Table 1. As seen from the table, the proposed method outperforms all the other methods. This indicates the ability of the proposed method in performing well in the presence of large illumination variations.

Next, the proposed method was tested on the AR face dataset which consists of images with varying conditions such as illumination, expression and occlusions. From the database, images of 50 male and female persons were selected for the evaluation of performance. The images were scaled to a size of 40×30 and converted to grayscale prior to the experiment. The training dataset was chosen as the first image from the two sessions (1^{st} and 14^{th}), thus making 2 training images per person. The remaining images were used as the test/probe dataset. The performance

Table 1: The recognition accuracy in % when the experiments were conducted on the Yale B dataset.

Method	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5
Proposed	**100**	**100**	**85.45**	**78.46**	**97.06**
PCA	100	88.18	58.18	37.69	35.29
KFA	100	87.27	63.64	40	35.29
KPCA	85	65.45	40.91	28.46	32.35
GPCA	100	87.27	67.27	40	34.12
GKFA	100	87.27	68.18	37.69	34.12
GKPCA	100	82.72	65.45	33.85	31.76

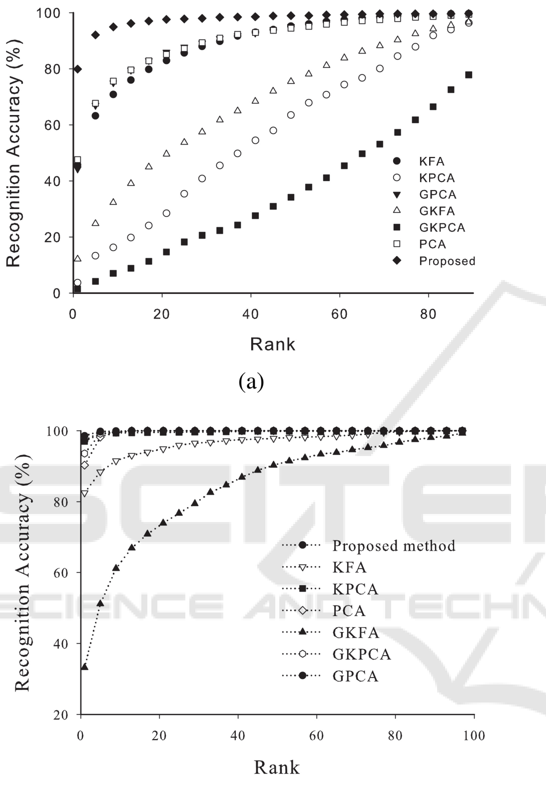


Figure 4: The cumulative matched curves for the various methods when tested on the (a) AR face database and (b) PUT face database.

analysis is given in Fig. 4(a). The higher recognition accuracy of the proposed method compared to the other methods indicates its capability to perform even in the presence of illumination invariance and outliers due to occlusions.

To test the robustness of the proposed method against pose variations, the PUT face database was used. The images were downscaled to 40×30 and converted to grayscale for evaluating the performance. Because of the presence of variations in pose, the training set was constructed by selecting two images and then creating different templates from these two images by shifting the images horizontally and

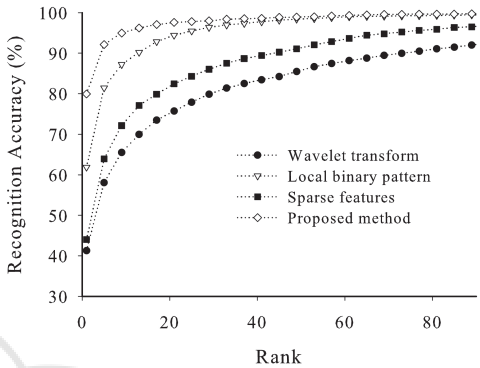


Figure 5: A comparison of cumulative matched curves when using features from wavelet transform, local binary pattern, sparse features and that of the proposed method.

vertically. The rest of the images in the dataset were used for testing the performance. The result of the performance evaluation is shown in Fig. 4(b). Here also, the proposed method is seen to surpass the performance of the other methods.

Fig. 5 shows the recognition accuracy when face recognition is performed on the AR face database using wavelet based template matching, local binary pattern, sparse distributed features and the proposed method. The graph clearly indicates the performance improvement obtained by combining the individual methods.

4 CONCLUSION

The paper proposes a combination of feature processing approaches to arrive at a set of discriminative sparse features for addressing the problem of low resolution face recognition. The proposed method makes use of the principles of wavelet transform, local binary pattern and sparse based feature extraction technique for efficiently representing the human facial features. The features extracted are classified using a minimum distance classifier with Shepard's similarity measure as the distance measure. The experimental results demonstrates the proposed method's capacity to perform low resolution face recognition in the presence of variations such as illumination, occlusions and pose. The presence of wavelet transform and local binary pattern attributes to the proposed method's capability in nullifying variations in the face image caused by illumination effects while the sparse feature representation and the Shepard's similarity measure based nearest neighbour classification provided the efficient elimination of data outliers. The proposed technique can find application in image recognising situations demanding the use of low resolution image, limited storage and low power smart devices.

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