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Face Verification Using Local Binary Patterns and Sparse Representation Techniques

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Abstract— **We present a novel method of face verification which is based on the concept and principles of sparse representation of signals. The sparse representation techniques are used in both feature extraction and classification steps. The proposed method is relatively invariant to changes in imaging conditions such as illumination variations. This is due to the characteristics of the sparse sampling method. In order to improve the invariance properties of the system, the feature extraction algorithm is motivated by using the Local Binary Pattern (LBP) features. Our experimental studies on the XM2VTS and XM2VTS-DARK datasets demonstrate that the proposed method improves the performance of the verification system.**

Keywords— ***Face Verification; Sparse Representation; Sparsity Preserving Projection (SPP); Sparse Representation Classifier (SRC); Local Binary Pattern(LBP)***

I. INTRODUCTION

Identity verification is an active research area which has many applications in real life. The main purpose of an identity verification system is to identify the person who has the true claimant of the person who is an impostor. Face is an important modality which is widely used in verification systems [1]. One of the most important challenges in a face verification system is how to deal with the variations of face images. The main sources of the variations are the variation in lighting conditions, camera quality, pose, expression, race and age. In this research study, the sparse representation (SR) based techniques are used in order to improve the performance of a verification system. The main idea is to extract more informative and abstract features from the face images and in the same time establish an effective classifier.

Feature extraction and decision making are two important steps of object recognition systems in general and face recognition systems in particular. In feature extraction step, the main goal is to extract the features which contain the most representative and discriminative information. Dimensionality reduction is the other important objective of the feature extraction step. Unsupervised and supervised methods such as the Principle Component Analysis (PCA) [2] and Linear Discriminant Analysis (LDA) [3] are two main groups of feature extraction techniques. The sparse sampling based approaches are among the recently developed feature extraction methods. Both supervised [4,5,6] and unsupervised [7,8] techniques have been adopted for developing the sparse sampling based feature extraction methods. From another point of view, feature extraction methods can be divided into the global and local approaches. In the global methods, the features are extracted from the whole image. In contrast, in the local methods, the features are derived from some local areas of the image. The variations caused by partial occlusion, directional lighting, facial expression etc. usually have an effect on just some parts of the image. So, the local approaches are usually less sensitive to these variations. On the other hand, these methods are more sensitive to the object (face) localisation error. An appropriate combination of the local and global methods usually leads to better results. In this study, we adopted the use of a local feature extraction method which is based on the Local Binary Pattern (LBP) codes for deriving the local information [9]. The local features are then combined using the adopted sparse representation based technique.

The main purpose of the classification step of a recognition system is to design the simplest (low computational complexity) and most effective (low error rate) decision making system.

Within the framework of face verification problem, our main idea for applying the sparse representation techniques is to firstly build the clients models by the $l1$ regularization of an objective function. In this step, either the original gray level values of face images or their extracted LBP features can be utilised. The basis vectors of the feature space are then calculated using the constructed models. Finally, an optimal classifier is designed in the resulted feature space. We apply sparse representation based techniques in both feature extraction and classification steps of the face verification system. Our experimental studies were conducted on the XM2VTS and XM2VTS-DARK datasets. It is shown that the performance of the verification system is highly improved by applying the sparse representation based methods. More improvement is obtained by using the LBP features within the framework of the proposed verification system.

The rest of the paper is organised as follows. In Section 2, some of the most important related works are briefly reviewed. In Sections 3 and 4, we give more details about the adopted methods of feature extraction; the sparse representation based method and the LBP based method. In Section 5, the Sparse Representation based Classifier (SRC) is discussed. In Section 6, we present our SR based face verification system. The experimental results are reported in Section 7 and finally some conclusions are drawn in Section 8.

II. Related Works

Recently, due to progresses in feature extraction and classification algorithms, face recognition systems have extensively developed. In this work, in order to improve the performance of the identity verification system, a combination of feature extraction using the Local Binary Pattern (LBP) technique and classification using the sparse representation algorithm has been adopted. In this section, recent developments in the abovementioned research areas are briefly reviewed.

A. Local Binary Patterns in Face Recognition Systems

Local Binary Patterns (LBP) technique, after its introduction as a texture representation method in 1994 [10], has found a broad range of applications in the field of image processing in general and in the area of face recognition in particular. One of the most important recent advancements in this field was achieved by Heikkila et al. in 2009 when a combination of the SIFT features and the LBP operator was introduced for describing the interest regions of an image. The resulting descriptor is then used in the contexts of image matching and object category classification [11].

Ahonen et al. proposed a rotation invariant image descriptor by computing discrete Fourier transform of the LBP histograms [12]. In [13], a face verification system has been designed which exploits the characteristics of the features derived from the Gabor filters and LBP operator. A similar idea has been adopted in [14] where the LBP operator and wavelet transform are combined for improving the performance of an identity verification system.

Zhang et al. proposed a second order version of the Local Binary Pattern called Local Derivative Pattern (LDP). Within the framework of a face verification system, the performance of the LBP and LDP operators using gray level and Gabor features has been compared and it is shown that the high-order LDP operator outperforms the LBP one for both face identification and face verification [15].

In [16], a set of enhanced local texture features has been suggested by combining the KPCA and LBP algorithms. It is shown that these features improve the stability and efficiency of a face verification system in case of unwanted lightning changes.

In a few research studies on face verification, such as in [17], the idea of applying the LBP based algorithms to colour images has been taken into account.

B. Sparse Representation based Face Recognition

After introducing the idea of sparse representation of signals, in 2009 the Sparse Representation based Classifier (SRC) was proposed by Wright et al. [18]. Meanwhile, in the pattern recognition community, a number of research studies were performed on developing feature extraction algorithms using the sparse representation techniques. In this study, the Sparse Preserving Projection (SPP) algorithm is applied for feature extraction [7]. This method is, in fact, the basis of the other sparse representation based feature extraction techniques such as GSRP, DIET, LSPP, SLSPP and OSPP [4-8]. All the aforementioned methods were suggested to improve the efficiency of recognition systems.

In a pattern recognition system, as far as the feature extraction step is concerned with, the preferred set of features is the one which have high within class correlation and low correlation between different classes. In face recognition systems, the within class variations is due to factors such as illumination variation, error in face area registration, facial expression, aging and face pose variations. In this study, we adopted the use of the LBP based features in order to reduce the effects of factors like the illumination changes and miss-registration problem. In fact, by applying the LBP operator, face images are described by their texture rather than their gray level values. The texture information is significantly less sensitive to the above mentioned factors. The sparse representation based techniques are also useful to reduce some of these effects by eliminating partial redundancy among the data. Also, seeking for the sparsest representation automatically increases the between classes discriminations [18].

III. SPARSE REPRESENTATION FEATURE EXTRACTION

The main purpose of linear dimensionality reduction approaches is to generate a projection matrix, $\mathbf{W} \in \mathrm{R}^{n \times k}$, which maps the original n-dimensional data to a new k-dimensional feature space where $k \ll n$. The most popular methods of linear feature extraction are PCA and LDA. The main idea of the PCA algorithm is to map a dataset to a lower dimensional representation space while retaining as much as possible of the variation present in the dataset. It is obtained by calculating the Eigen-vectors corresponding to the k largest Eigen-values of the covariance matrix of the dataset. The main problem of this method is that the diversity of both between-class and within-class are equally considered in the projection matrix. For solving this problem, in the LDA method between-class scattering is maximized while the within class one is minimized.

Due to the considerable expansion of the Sparse Representation (SR) theory and its applications in data compression [19], detection theory [20], probability theory [21] and pattern recognition [22, 23], a variety of the SR based techniques has been recently proposed. The Sparsity Preserving Projection (SPP) is among the developed feature extraction algorithms. It has been shown that the features derived from the SPP is largely invariant to rotation, scaling and translation and contain natural discriminating information [7].

A. Sparse Representation

Let $\mathbf{x}_i$ be an n-dimensional feature vector. In the case of image data, this feature vector can be generated by concatenating the image rows or columns. Also, let matrix $\mathbf{D} \in \mathrm{R}^{n \times k}$ be an over-complete dictionary. The goal of the SR approaches is to represent an input signal in terms of the minimum number of dictionary columns.

$$\min_s \|\mathbf{s}\|_0 \qquad \mathbf{x} = \mathbf{D}\mathbf{s} \tag{1}$$

where $\mathbf{s} \in R^k$ and $\| \ \|_0$ is the pseudo-l_0 norm which is equal to the number of non zero atoms. Since this equation is a non-convex problem, it is usually converted to an l_1 norm form:

$$\min_s \|\mathbf{s}\|_1 \qquad \mathbf{x} = \mathbf{D}\mathbf{s} \tag{2}$$

In many practical problems, the original signal, $\mathbf{x}$, is noisy. Therefore, the following equation is instead used:

$$\min \|\mathbf{s}\|_1 \qquad \|\mathbf{x} - \mathbf{D}\mathbf{s}\|_2 \le \varepsilon \tag{3}$$

where ε is the acceptable error rate.

B. Sparsity Preserving Projection

The main goal of the Sparsity Preserving Projection (SPP) method is to design a projection matrix which preserves as much as possible the sparse reconstructive relations between the training samples.

Given a set of training samples $\{\mathbf{x}_i\}_{i=1}^k \in R^n$, an over-complete dictionary which contains the training samples as its columns can be formed: $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k]$. Using Equation 2 or 3, the pseudo-sparse representation of each sample can be calculated:

$$\min \|\mathbf{s}_i\|_1 \qquad \|\mathbf{x}_i - \mathbf{X}\mathbf{s}_i\|_2 \le \varepsilon$$
$$1 = \sum_i \mathbf{s}_i \tag{4}$$

where $\mathbf{s}_i = [\mathbf{s}_{i1}, ..., \mathbf{s}_{ii-1}, 0, \mathbf{s}_{ii+1}, ..., \mathbf{s}_{ik}]^T$ is a k-dimensional vector. It should be noted that the ith element of $\mathbf{s}_i$ is forced to be zero. In fact, the main goal is to achieve the best representation of $\mathbf{x}_i$ versus all the other dictionary elements. Note that s_{ik} indicates the relationship between the ith training sample and the kth training sample. If we suppose that $\mathbf{x}_i^j$ be the ith training sample from the jth class, it is expected that $\mathbf{x}_i^j = 0.\mathbf{x}_1^1 + ... + \alpha_{ii-1}\mathbf{x}_{i-1}^j + \alpha_{ii+1}\mathbf{x}_{i+1}^j + ... + 0.\mathbf{x}_n^c$ where c is the number of classes. In practice, the coefficients which are related to the samples from the other classes have very small values. This representation indicates that discriminative information is preserved correctly.

After computing the above pseudo sparse representation of the training samples, the sparse reconstructive weight matrix, $\mathbf{S}$, is determined:

$$\mathbf{S} = [\tilde{\mathbf{s}}_1, \tilde{\mathbf{s}}_2, ..., \tilde{\mathbf{s}}_n] = (\tilde{\mathbf{s}}_i)_{k \times k} \tag{5}$$

where $\tilde{\mathbf{s}}_i$ is the resulted solution of Eq. 4 for the ith training sample. The optimal linear projective matrix, $\mathbf{W}$, is finally calculated by:

$$\mathbf{w} = \arg\min_{\mathbf{w}} \sum_{i=1}^{N} \left\| \mathbf{w}^{\mathrm{T}}\mathbf{x}_i - \mathbf{w}^{\mathrm{T}}\mathbf{X}\mathbf{s}_i \right\|$$
$$\mathbf{w}^{\mathrm{T}}\mathbf{X}\mathbf{X}^{\mathrm{T}}\mathbf{w} = \mathbf{1} \qquad (6)$$

The later constraint guarantees that there exists a stable solution. A matrix form of the above equation is:

$$\mathbf{w} = \arg\min_{w} \mathbf{w}^{\mathrm{T}}\mathbf{X}(\mathbf{I} - \mathbf{S} - \mathbf{S}^{\mathrm{T}} + \mathbf{S}\mathbf{S}^{\mathrm{T}})\mathbf{X}^{\mathrm{T}}\mathbf{w}$$
$$\mathbf{w}^{\mathrm{T}}\mathbf{X}\mathbf{X}^{\mathrm{T}}\mathbf{w} = \mathbf{1} \qquad (7)$$

It is shown that the solution of this equation is the eigenvectors associated to the k smallest Eigen-values of matrix $(\mathbf{X}\mathbf{X}^{\mathrm{T}})^{-1}(\mathbf{X}(\mathbf{I} - \mathbf{S} - \mathbf{S}^{\mathrm{T}} + \mathbf{S}\mathbf{S}^{\mathrm{T}})\mathbf{X}^{\mathrm{T}})$.

Note that for high dimensional datasets such as image data, the matrix $\mathbf{X}\mathbf{X}^{\mathrm{T}}$ is usually near-singular. So, the images are first projected into a lower dimensional feature space using for example the PCA algorithm. The projection matrix of the SPP is then calculated.

IV. LOCAL BINARY PATTERN

Local Binary Pattern (LBP) is a powerful method for describing the texture information in digital images. The LBP operator acts in relation to the neighbours of a pixel. Suppose c and N respectively refers to a pixel of the image and the set of associated neighbouring pixels. Considering the gray level value of c as the threshold, if the gray level value of each neighbouring pixel is larger than the threshold, the neighbour is coded as "1". Otherwise, a "0" value is considered. The binary pattern corresponding to the central pixel is then obtained by concatenating the "0" and "1"s.

Various structures can be used for defining the neighbours of a pixel. As shown in Figure1, the easiest way is the well known 8-neighbourhood structure. The resulted LBP code can be determined using the following equation:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n s(i_n - i_c) \qquad (8)$$

where (x_c, y_c) refers to the central pixel coordinates. Also, i_c and i_n refer to the gray level values of the central and neighbouring pixels respectively. $s(x)$ is defined as:

$$s(x) = \begin{cases} 1 & , \quad x \geq 0 \\ 0 & , \quad x < 0 \end{cases} \qquad (9)$$

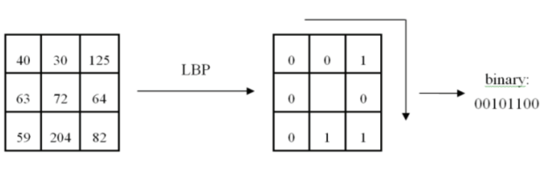

Figure 1.LBP code for the 8-neighbourhood structure

The other widely used neighbouring structure is a circular structure where a circle of radius R centred at the under-processed pixel is considered and P equally distance sample points on the border of the circle are determined as the neighbours. The values of R and P have to be selected properly.

Uniform pattern is an important concept which is used for describing texture information within the framework of the local binary pattern methods [9]. Using this concept, objects attributes which contain a greater differentiation such as edges, corners and spots are well described. Moreover, the computational complexity of the associated LBP algorithm is reduced. In order to introduce the uniform pattern, the U scale of a binary pattern is introduced first. The U scale represents the number of transitions from 0 to 1 and vice versa. For example, the U value of binary patterns 00000000_2 and 11111111_2 are equal to zero and 11100111_2 has a U value of two. Accordingly, $LBP^{u_2}_{P,R}(x, y)$ operator is introduced as follows:

Patterns with a U value of less than or equal to 2 are considered as separate patterns. The other patterns (U>2) are considered as a same pattern. So, if the neighbourhood size is equal to P, then $(P-1)P+3$ separate patterns would be available; $(P-1)P+2$ of which are related to the uniform patterns and the last one is for the others.

In this research, for extracting the LBP based features of an image, using the $LBP^{u_2}_{P,R}(x, y)$ operator the LBP codes corresponding to the image pixels are calculated. The image is then divided into small rectangular areas and in each area the associated LBP histogram is computed. The LBP based feature vector is finally determined by concatenating the local histograms.

V. SPARSE REPRESENTATION BASED CLASSIFIER

In this section, within the framework of a verification system, the sparse representation based classifier (SRC) [18] is reviewed.

Suppose $\tilde{\mathbf{x}}_i^j$ be the features derived from the ith training sample of the jth class. The over-complete dictionary matrix, $\tilde{\mathbf{X}} = [\tilde{\mathbf{x}}_1^1 \quad \tilde{\mathbf{x}}_2^1 \quad \ldots \quad \tilde{\mathbf{x}}_{n_1}^1 \quad \tilde{\mathbf{x}}_1^2 \quad \ldots \quad \tilde{\mathbf{x}}_{n_c}^c]$ can be calculated using the training dataset where c is the number of classes and n_j is the number of training examples of the jth class. Now, suppose that $\tilde{\mathbf{y}}^j$ is the feature vector derived from a new sample where j is the claimed identity. Using Eq. 2 or 3, the sparse representation of the sample, $\tilde{\mathbf{s}}_i$, can be calculated. So:

$$\tilde{\mathbf{y}}_i^j = \tilde{\mathbf{s}}_i \tilde{\mathbf{X}}^T \qquad (10)$$

If the number of training examples per each class is large enough, it should be possible to describe the new sample by a linear combination of the training examples of the associated class *(j)*. So, if the sample truly belongs to the jth class, we expect that only those coefficients of $\tilde{\mathbf{s}}_i$ which are related to the jth class be non-zero. The others should be almost zero. Therefore, the other components of $\tilde{\mathbf{s}}_i$ are set to zero:

$$
\begin{aligned}
\tilde{\mathbf{s}}_i &= [\tilde{s}_1^1, \dots, \tilde{s}_{n_1}^1, \dots, \tilde{s}_1^j, \dots, \tilde{s}_{n_j}^j, \dots, \tilde{s}_1^c, \dots, \tilde{s}_{n_c}^c] \\
&\Downarrow \\
\tilde{\mathbf{s}}'_i &= [0, \dots, 0, \dots, \tilde{s}_1^j, \dots, \tilde{s}_{n_j}^j, \dots, 0, \dots, 0]
\end{aligned}
\tag{11}
$$

We can now reconstruct the related feature vector using the over-complete dictionary and the new sparse vector $\tilde{\mathbf{s}}'_i$:

$$\tilde{\mathbf{y}}^j_{i,rec} = \tilde{\mathbf{s}}'_i \tilde{\mathbf{X}}^T \tag{12}$$

The similarity between $\tilde{\mathbf{y}}^j_{i,rec}$ and $\tilde{\mathbf{y}}^j_i$ is then computed. If the sample is really from the jth class, the similarity score would be high enough and the claim would be accepted. Otherwise, it is rejected.

VI. FACE VERIFICATION BY SPARSE REPRESENTATION TECHNIQUES

Figure 2 demonstrates the block diagram of the adopted face verification system. As shown, the verification system consists of three main subsystems: "face image acquisition and pre-processing", "feature extraction" and "decision making". The first stage involves sensing and image pre-processing, the result of which is a geometrically registered and photometrically normalised face image. In the next stage, the face data is projected into a feature space. The final stage of the face verification process involves matching and decision making.

As mentioned earlier, we use the SR based techniques in both feature extraction and classification steps of the verification system. The SPP method is applied for the feature extraction. Suppose that k face images per each client are available for training of the system. So, the associated over-complete dictionary will have $l = m \times k$ columns where m is the number of clients. The projection matrix, $\mathbf{W}_{SPP}$, is obtained using the SPP method. The training and test data are then projected into the resulted feature space. Therefore, the final over-complete dictionary matrix would be $\tilde{\mathbf{X}}_{SPP} \in R^{n' \times l}$ where n' is the number of dimensions of the SPP space.

The SRC algorithm is used for decision making. In the evaluation/test step, the face data is projected into the SPP space and the similarity between the original feature vector and the reconstructed one (as it was discussed in Section V) is calculated. In this study, two different similarity measure/distance metric, the Euclidean (Eu) distance and Normalised Correlation (NC) measure were applied:

$$d\,s_{Eu} = i\sqrt{(y^j_{1,rec} - x^j_{1,SPP})^2 + \dots + (y^j_{l,rec} - x^j_{l,SPP})^2} \tag{13}$$

$$dis_{NC} = \frac{\mathbf{y}^j_{rec} . \mathbf{x}^j_{SPP}}{\left\|\mathbf{y}^j_{rec}\right\| . \left\|\mathbf{x}^j_{SPP}\right\|} \tag{14}$$

The Similarity value is finally compared with a predetermined threshold in order to make the decision. The desired threshold is calculated using an evaluation dataset based on the equal error rate criterion. In fact, in a verification system, we deal with two kinds of error, either a true client is rejected (False Rejection) or an impostor is accepted (False Acceptance). Clearly, the False Acceptance Rate (FAR) and False Rejection Rate (FRR) depend on the threshold value. By equal error rate, we mean the point in which the false acceptance rate is equal to the false rejection rate. The adopted threshold is finally used in the evaluation and test stages for calculating the associated errors. Figure 3 shows examples of the clients and impostors scores histograms. The associated EER point is also shown in the figure.

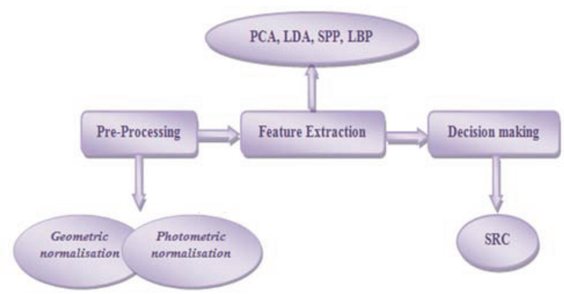

Figure 2. Block diagram of the face verification system

VII. EXPERIMENTS

We conducted our face verification experiments on the XM2VTS and XM2VTS-DARK data sets. Figure 4 contains examples of the geometrically registered and photometrically normalised images of these databases. In this study, the face images are geometrically normalised utilising the manually annotated eyes positions. The histogram equalisation algorithm is used for photometric normalisation.

The XM2VTS database [24] consists of 2360 face images of 295 individuals. The face images were taken from 4 video recording sessions, 2 images per session. Based on the Lausanne protocol, 200 subjects have been considered as the system clients. The others act as the impostors; 25 subjects for the evaluation and 70 subjects for the test stages. Two experimental configurations have been designed in the Lausanne protocol. Tables I and II specifies these configurations. Also, the XM2VTS-DARK database contains 4 images per person from the same subjects. In 2 recordings, the lighting was done from the right side and in the others from the left.

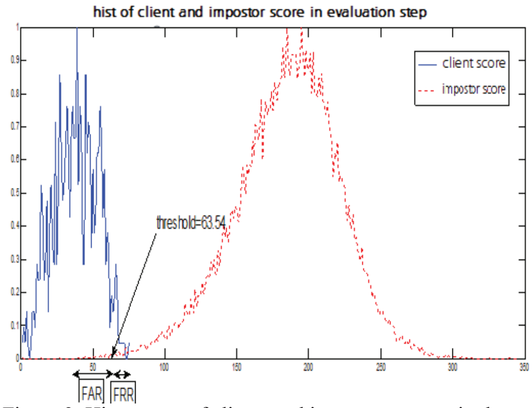

Figure 3. Histograms of clients and impostors scores in the evaluation step

We performed two groups of experiments using the dark data. In the first group (un-matched scenario), the XM2VTS data were used for training and evaluation and the dark data were used in the test step (*dark 1*). In the other group (dark-matched scenario), the dark data were used for clients modelling, evaluation and test (*dark 2*). In the case of the XM2VTS and the first group of the dark experiments, because of the constraints imposed by the Lausanne protocol, no statistical analysis of the results was performed. But, in the case of the *dark 2* experiments, different experimental configurations as shown in Table III were considered. So, in this case, the statistical characteristics of the results (mean and variance) are reported.

As the feature extraction tool, we applied 3 different methods: the PCA, LDA and SPP algorithms. Also, for the classification purpose, we applied the Euclidean (Eu) distance and Normalised Correlation (NC) measure. These measures were used both directly and within the framework of the SRC algorithm. Table IV contains the results without applying the SRC algorithm. The values in this table are the Half Total Error Rate (HTER), i.e. the average value of the FAR and FRR. These results demonstrate that although the system which is based on the LDA and NC measure leads to relatively good results, the SPP features along with the Eu metric is superior. Note that the SPP is an unsupervised method while the LDA is a supervised approach.

Table V contains results of the similar experiments using the SRC method. As expected, applying the Euclidean distance metric always leads to better results when the sparse representation based methods are used for feature extraction or/and classification. This is due to the nature of the *l2* norm which is used for the data reconstruction within the framework of the sparse representation method. It can be seen that, overall, the best performance is obtained using the SPP features along with the Euclidean distance based SRC algorithm.

The verification experiments were then repeated using the LBP features. The SRC method along with the Eu distance metric was used for the classification purpose. Table VI contains the associated results. It can be seen that the performance of the system is more improved using the LBP features especially in the case of the dark data. In order to more easily visualise and compare the results, the verification error has been shown in the plots of Figures 5 to 8. In these plots, results using the Gray scale and LBP features have been shown. These results demonstrate that the proposed verification system which is based on the LBP and sparse representation based techniques is relatively robust to the illuminations variations. As mentioned earlier, this is due to this fact that by applying the LBP operator, face images are described by their texture which is significantly less sensitive to these variations. Also, the sparse representation based techniques reduce the effects of within class variations by eliminating partial redundancy among the data. Moreover, seeking for the sparsest representation automatically increases the between classes discriminations.

It has to be noted that an important issue in the SPP algorithm is determining the optimum number of dimensions. In this work, the optimum number of dimensions is determined in the evaluation stage by looking for the minimum number of dimensions after which by adding more features the performance of the system is not significantly improved. Figures 9 to 12 contain the associated plots for the SPP algorithm using the LBP based features. In these figures, the HTER value versus the number of dimensions using the evaluation and test data has been shown. These plots show that the evaluation and test results are consistent. Therefore, it is convincing to find the optimum number of dimensions in the evaluation step.

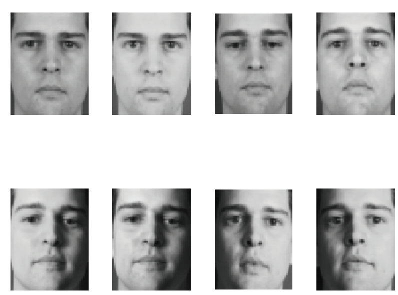

Figure 4. Top row: Examples of the XM2VTS data, Lower row: Examples of the XM2VTS-DARK data

TABLE I. LAUSANNE PROTOCOL FOR XM2VTS DATABASE, CONFIGURATION1

Session	Shot	200	25	70
1	1	Train	Impostor-Eval	Impostor-Test
	2	Client-Eval		
2	1	Train		
	2	Client-Eval		
3	1	Train		
	2	Client-Eval		
4	1	Client-test		
	2			

TABLE II. LAUSANNE PROTOCOL FOR XM2VTS DATABASE, CONFIGURATION2

Session	Shot	200	25	70
1	1	Train	Impostor-Eval	Impostor-Test
	2			
2	1	Train		
	2			
3	1	Client-Eval		
	2			
4	1	Client-Test		
	2			

TABLE III. THE EXPERIMENTAL CONFIGURATIONS OF *DARK2*

Shot	1	2	3	4
Lighting Direction	Left	Left	Right	Right
200 Subject	Train	Client Evaluation	Train	Client Test
25 Subject	Impostor Evaluation			
70 Subject	Impostor Test			

Shot	1	2	3	4
Lighting Direction	Left	Left	Right	Right
200 Subject	Client Evaluation	Client Test	Train	Train
25 Subject	Impostor Evaluation			
70 Subject	Impostor Test			

Shot	1	2	3	4
Lighting Direction	Left	Left	Right	Right
200 Subject	Train	Train	Client Evaluation	Client Test
25 Subject	Impostor Evaluation			
70 Subject	Impostor Test			

Shot	1	2	3	4
Lighting Direction	Left	Left	Right	Right
200 Subject	Train	Client Test	Train	Client Evaluation
25 Subject	Impostor Evaluation			
70 Subject	Impostor Test			

TABLE IV. ERROR RATE WITHOUT SRC

Without SRC		PCA		LDA		SPP	
		HTERE	HTERT	HTERE	HTERT	HTERE	HTERT
Euclidean distance	XM2VTS1	14.3%	14.12%	7.56%	7.34%	2.3%	2.7%
	XM2VTS2	8.98%	9.37%	7.95%	7.39%	1.79%	1.93%
	DARK1	17.6%	17.67%	8.23%	8.37%	5.9%	5.69%
	DARK2	21.03% ±0.03	22.96% ±0.03	12.13% ±0.20	11.9% ±0.21	7.38% ±0.21	6.99% ±0.21
Angle distance	XM2VTS1	5.72%	5.36%	2.5%	2.9%	3.67%	3.9%
	XM2VTS2	9.47%	8.83%	9.6%	7.92%	19.5%	21.62%
	DARK1	10.3%	11.98%	7.39%	7.21%	7.41%	7.38%
	DARK2	13.67% ±0.31	13.55% ±0.31	9.21% ±0.310	9.95% ±0.310	10.36% ±0.310	10.87% ±0.30

TABLE V. ERROR RATE CONSIDERING THE SRC AND GRAY VALUE FEATURES

With SRC		PCA		LDA		SPP	
		HTERE	HTERT	HTERE	HTERT	HTERE	HTERT
Euclidean distance	XM2VTS1	5.09%	5.02%	4.44%	5.07%	0.05%	0.07%
	XM2VTS2	0.001%	4.3%	0.28%	5.40%	0.001%	0.03%
	DARK1	7.6%	7.2%	4.35%	5.01%	1.69%	1.4%
	DARK2	13.4% ±0.001	12.8% ±0.010	10.4% ±0.010	9.9% ±0.011	6.4% ±0.001	5.67% ±0.001
Angle distance	XM2VTS1	1.27%	1.9%	0.62%	0.6%	5.3%	5.5%
	XM2VTS2	2.5%	2.9%	4.2%	6.1%	3.0%	3.8%
	DARK1	3.2%	3.01%	2.7%	2.35%	2.57%	2.98%
	DARK2	9.4% ±0.11	8.7% ±0.01	7.5% ±0.010	7.34% ±0.010	11.2% ±0.010	10.0% ±0.023

TABLE **VI.** Error rate considering the SRC and LBP based features

With SRC & LBP		PCA		LDA		SPP	
		HTERE	HTERT	HTERE	HTERT	HTERE	HTERT
Euclidean distance	XM2VTS1	2.88%	3.41%	0.012%	0.037%	0.039%	0.016%
	XM2VTS2	0.001%	0.04%	0.001%	0.047%	0.01%	0.02%
	DARK1	4.43%	13.31%	0.005%	1.37%	0.25%	2.04%
	DARK2	4.43% ±0.065	23.35% ±0.065	0.005% ±0.015	2.38% ±0.015	0.25% ±0.313	2.65% ±0.070

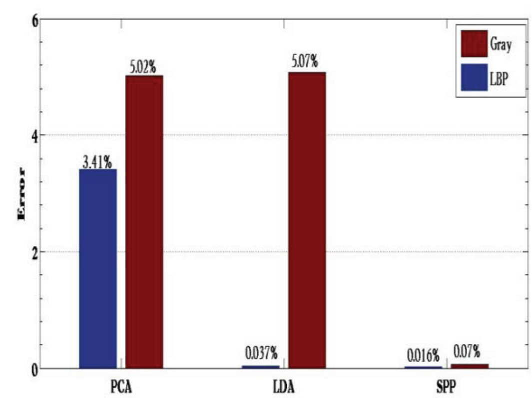

Figure 5. Verification error for the gray scale and LBP based features using the SRC method and Eu metric (XM2VTS1)

VIII. CONCLUSION

In this paper, we presented a face verification system which is based on the sparse representation methods. The SPP technique is used for feature extraction and the SRC algorithm is applied for the classification. Our experimental studies show that the proposed method leads to an almost error-free system in controlled conditions. A relatively low error rate occurs in uncontrolled illumination conditions. The performance of the system is more improved by using the Local Binary Pattern features within the framework of the proposed system. In the future studies, we would like to examine the performance of the proposed approach on more complicated scenarios. As mentioned in Section II, different modifications have been applied on the LBP and Sparse Representation based feature extraction. Investigating the effects of those methods within the framework of the proposed face verification algorithm is the other matter of interest in the future studies.

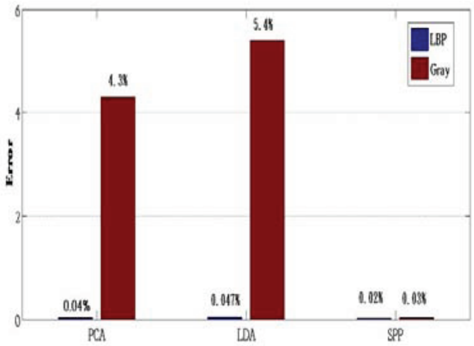

Figure6. Verification error for the gray scale and LBP based features using the SRC method and Eu metric (XM2VTS2)

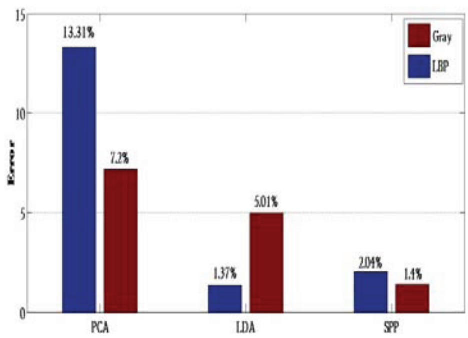

Figure 7. Verification error for the gray scale and LBP based features using the SRC method and Eu metric (Dark1)

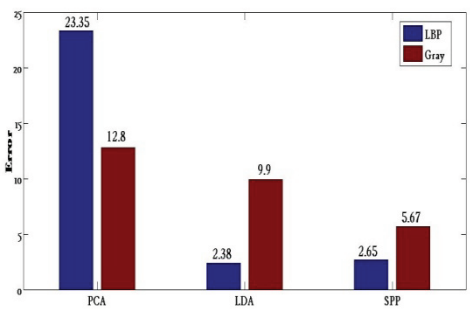

Figure 8. Verification error for the gray scale and LBP based features using the SRC method and Eu metric (Dark2)

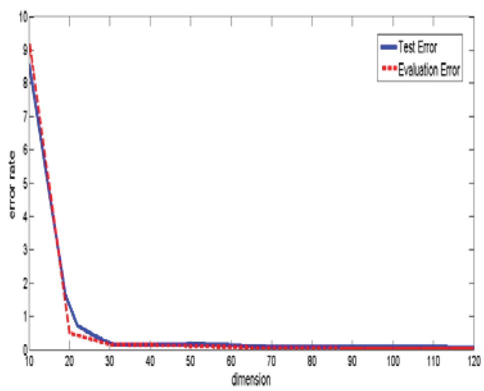

Figure 9. Verification error vs. the number of dimensions considering the evaluation and test data (LBP, SPP and SRC for XM2VTS1)

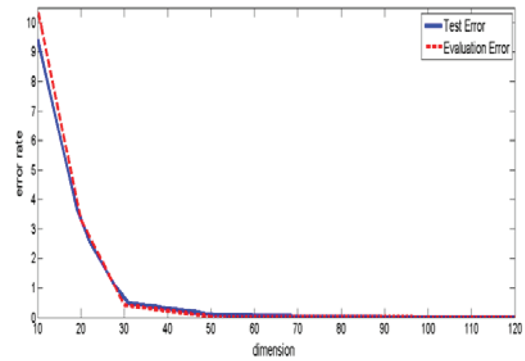

Figure 10. Verification error vs. the number of dimensions considering the evaluation and test data (LBP, SPP and SRC for XM2VTS2)

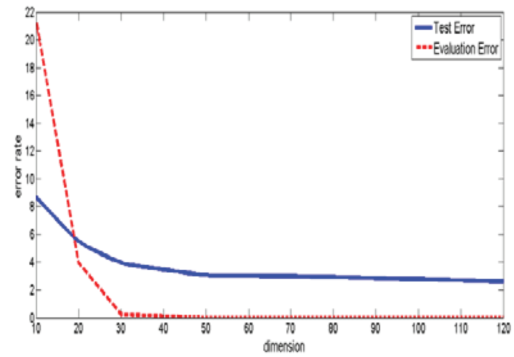

Figure 11. Verification error vs. the number of dimensions considering the evaluation and test data (LBP, SPP and SRC for dark1)

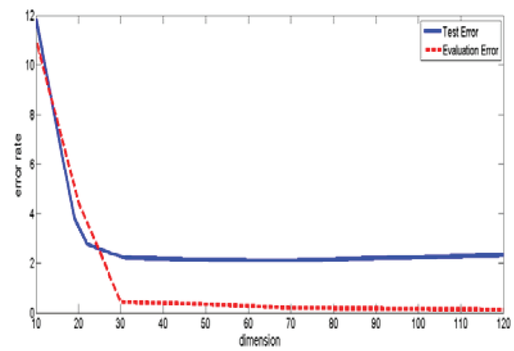

Figure 12. Verification error vs. the number of dimensions considering the evaluation and test data (LBP, SPP and SRC for dark2)

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