USING COLOUR LOCAL BINARY PATTERN FEATURES FOR FACE RECOGNITION

Jae Young Choi[1], *Konstantinos N. Plataniotis*[2], *Yong Man Ro*[1]

[1]Image and Video System Laboratory, Korea Advanced Institute of Science and Technology (KAIST), Yuseong-Gu, Daejeon, 305-701, Korea, [2]The Edward S Rogers Sr Department of Electrical and Computer Engineering, University of Toronto, Toronto, Ontario, M5S 3GA, Canada

ABSTRACT

In this paper, we propose a novel feature representation based on color-based Local Binary Pattern (LBP) texture analysis for face recognition (FR). The proposed method exploits both color and texture discriminative features of a face image for FR purpose. We evaluate the proposed feature using three public face databases: CMU-PIE, Color FERET, and XM2VTSDB. Experimental results show that the results of the proposed feature impressively better than the results of grayscale LBP and color features. In particular, it is shown that the proposed feature is highly robust against severe variations in illumination and spatial resolution.

Index Terms**—** Face recognition, color texture, Local Binary Pattern (LBP), color space, color LBP features

1. INTRODUCTION

Face recognition (FR) has received a significant interest in pattern recognition and computer vision due to the wide range of applications including video surveillance, biometric identification and face indexing in multimedia contents. As in any classification task, feature extraction is of prime importance in face recognition process. Recently, the Local Binary Pattern (LBP) [1] has gained reputation as a powerful texture feature (or descriptor) for face recognition. The LBP-based face feature has proven to be highly discriminative due to different levels of locality and to be efficient due to its fast computation.

Thus far, numerous approaches for LBP-based face recognition have been developed and successfully used for improving FR performance. However, most of this work has been limited to *grayscale* texture analysis. Recently, there has been a limited but increasing amount of work on the color aspects of textured images, namely a *color texture* [2]-[3]. Results in these works indicate that color information can play an important role in a texture analysis and classification/recognition, and it can be used to considerably enhance classification/recognition performance.

Based on the above studies, effectively combining color and texture features (extracted from a color face image) is expected to lead to better FR performance than separately used color or texture features. However, at the moment, it remains open problem how to combine color and texture features for the purpose of improving FR performance. In this paper, we propose a novel feature representation based on color-based LBP operator for face recognition, referred to as the *color LBP feature* which exploits both color and texture discriminative features. Specifically, in our method, LBP-based texture feature, termed color LBP histogram, is independently extracted from each of the different color bands (or channels). Subsequently, each low-dimensional feature of a corresponding color LBP histogram is computed using popular low-dimensional feature extraction techniques such as Principal Component Analysis (PCA). Then, resulting low-dimensional features are concatenated to form a single feature vector, called by us color LBP feature.

Extensive experimental results on CMU-PIE, Color FERET, and XM2VTSDB show that the color LBP features can considerably improve FR performance, compared to FR approaches only using grayscale LBP features or color features. In particular, it is shown that, as opposed to grayscale LBP features, the color LBP features are highly robust against *uncontrolled illumination* (caused by the interruption of background colored light and cast shadow) and *small resolution images.*

The remaining of the paper is organized as follows: Section 2 presents the method for the extraction of the color LBP features. In Section 3, experimental results are presented followed by conclusions in Section 4.

2. EXTRACTION OF COLOR LBP FEATURES FOR FACE RECOGNITION

In this section, we first describe the way of computing channel-wise LBP histograms from different color bands and then outline a FR method making use of the proposed *color LBP feature* in the following subsections.

2.1. Computation of channel-wise color LBP histograms

In this section, we extend grayscale-based LBP operator to *color-based* LBP operator by incorporating chrominance information into a LBP analysis scheme. Let $\mathbf{I}$ be a red-green-blue (*RGB*) color face image with size N_h by N_w pixels. In order to extract the channel-wise color LBP histograms of $\mathbf{I}$, the $\mathbf{I}$ is first converted into images having different color representation (*e.g.,* a *RGB* color image is converted into a *YIQ* color image).

Let us assume that a total of K different *color component images* – resulting from color space conversion – are produced (*e.g.,* luminance (Y) or chrominance component (C_b or C_r) images in the YC_bC_r color space). Then, let $\mathbf{S}^{(i)}$ be the i^{th} color component image generated after the color space conversion. Subsequently, a gray level LBP histogram is separately and independently computed from each corresponding color component image ($\mathbf{S}^{(i)}$). Note that, in the computation of the color LBP histogram, uniform LBP operator is adopted because a typical

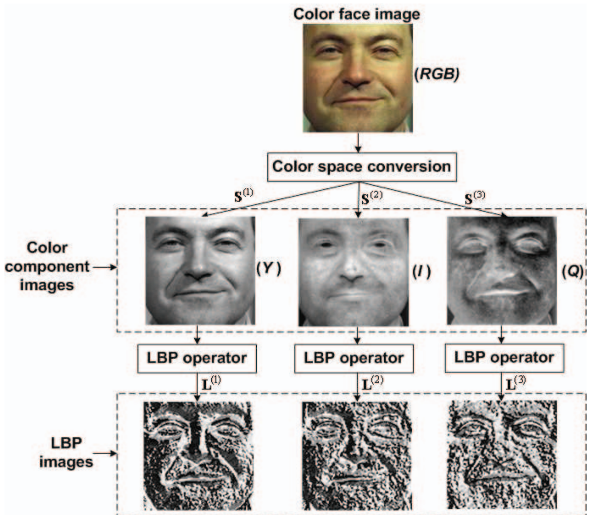

Fig. 1. Visualization of LBP operation process performed on each color component image. The text enclosed brackets (placed to the right-hand side of each face image) indicates that the grayscale or color format of the corresponding face images.

face image contains only a small number of LBP values (called uniform pattern) as reported in [4]. Then, the uniform LBP operator for the pixel (x, y) of $\mathbf{S}^{(i)}$ can be written as follows [4]:

$$LBP^{(i)}_{P,R}(x,y) = \begin{cases} \sum_{n=0}^{P-1} \delta(r_n^{(i)} - r_c^{(i)})2^n & \text{if } U^{(i)} \le 2 \\ P(P-1)+2 & \text{otherwise,} \end{cases} \tag{1}$$

where

$$U^{(i)} = |\,\delta(r_{P-1}^{(i)} - r_c^{(i)}) - \delta(r_0^{(i)} - r_c^{(i)})\,| + \sum_{n=1}^{P} |\,\delta(r_n^{(i)} - r_c^{(i)}) - \delta(r_{n-1}^{(i)} - r_c^{(i)})\,|, \tag{2}$$

and $\delta(x) = \begin{cases} 1 & x \ge 0 \\ 0 & x < 0 \end{cases}$, $r_n^{(i)}\,(n = 0,\ldots,P-1)$ denotes the color component values of P equally spaced pixels (or sampling points) on a circle of radius $R\,(R>0)$ that form a circular neighborhood of the center pixel (x, y) and $r_c^{(i)}$ denotes the color component value of pixel (x, y) of a circular neighborhood. Let $\mathbf{L}^{(i)}$ be a LBP image corresponding to $\mathbf{S}^{(i)}$. Note that each of the pixel values of $\mathbf{L}^{(i)}$ is filled with $LBP^{(i)}_{P,R}(x,y)$, defined by (1), at its given pixel location (x, y).

The aforementioned LBP operation process performed on each color component image from *YIQ* color space is illustrated in Fig. 1. To reflect and encode the *local properties* of a face image when computing its associated color histograms, $\mathbf{S}^{(i)}$ is divided into M small regions $\mathbf{S}^{(i,1)}, \mathbf{S}^{(i,2)}, \ldots, \mathbf{S}^{(i,M)}$ using the partition approach proposed in [1]. Then, a histogram for the j^{th} local region $\mathbf{S}^{(i,j)}\,(j = 1,\ldots,M)$ of the $\mathbf{S}^{(i)}$ is computed as follows:

$$h_k^{(i,j)} = \sum_{(x,y)\in \mathbf{S}^{(i,j)}} T\big(\mathbf{L}^{(i)}(x,y) = k\big), \quad k = 0,\ldots,L-1, \tag{3}$$

where

$$T(A) = \begin{cases} 1 & \text{if } A \text{ is true} \\ 0 & \text{if } A \text{ is false,} \end{cases} \tag{4}$$

and k denotes the k^{th} LBP label in the range $[0, L-1]$ and, therefore, $h_k^{(i,j)}$ is the number of pixels (with LBP label k) in the local region $\mathbf{S}^{(i,j)}$.

Using (3), regional LBP descriptor for the $\mathbf{S}^{(i,j)}$ can be expressed as follows:

$$\mathbf{h}^{(i,j)} = \left[h_0^{(i,j)}, h_1^{(i,j)}, \ldots, h_{L-1}^{(i,j)}\right]^{\mathrm{T}}, \tag{5}$$

where T stands for the matrix transpose operator, $\mathbf{h}^{(i,j)}$ is a standard column vector such that $\mathbf{h}^{(i,j)} \in \Re^L$ and $\Re^L$ denotes an $L-$ dimensional real space. Note that in (5) $\mathbf{h}^{(i,j)}$ provides regional LBP histogram information for $\mathbf{S}^{(i,j)}$. Finally, color LBP histogram for $\mathbf{S}^{(i)}$ can be obtained by concatenating $\mathbf{h}^{(i,j)}$ $(j = 1,\ldots,M)$ into a single column vector:

$$\mathbf{h}^{(i)} = \left[(\mathbf{h}^{(i,1)})^{\mathrm{T}}\ (\mathbf{h}^{(i,2)})^{\mathrm{T}} \cdots (\mathbf{h}^{(i,M)})^{\mathrm{T}}\right]^{\mathrm{T}}. \tag{6}$$

A set of K color LBP histograms $\mathbf{h}^{(i)}$ $(i = 1,\ldots,K)$ is applied to extract color LBP feature of a color face image used during face recognition process. Details for this process will be described in the following subsection.

2.2. Face recognition with color LBP features

Let $\mathbf{I}_{\mathrm{p}}$ be an unknown *RGB* color face image (to be identified or verified), which is denoted as a probe. In addition, let $\mathbf{G}$ be a gallery set consisting of prototype enrolled *RGB* color face images, each denoted by $\mathbf{I}_{\mathrm{g}}$, of known individuals (*i.e.,* $\mathbf{I}_{\mathrm{g}} \in \mathbf{G}$). Further, without any loss of generality, we denote the individual color LBP histograms of $\mathbf{I}_{\mathrm{p}}$ and $\mathbf{I}_{\mathrm{g}}$ by $\mathbf{h}_{\mathrm{p}}^{(i)}$ and $\mathbf{h}_{\mathrm{g}}^{(i)}$, respectively, where $i = 1,\ldots,K$. Note that, by using (6), $\mathbf{h}_{\mathrm{p}}^{(i)}$ and $\mathbf{h}_{\mathrm{g}}^{(i)}$ can be easily computed. Then, the K color LBP histograms are available for recognizing $\mathbf{I}_{\mathrm{p}}$, and thereby expecting better FR performance by combining multiple color LBP histograms based on information fusion theory [5] for pattern classification. Techniques for fusing multiple evidences (*i.e.,* multiple classification results or multiple features) can be largely classified into two classes: fusion at the level of features and fusion at the level of measurement (or matching score). It should be noted that, as reported in [5], it is widely accepted that feature-level information fusion can generally achieve better classification result than fusion methods working on other levels. Following above observation, we adopt information fusion techniques performed at the level of features.

Using feature-level information fusion techniques, color LBP feature of $\mathbf{I}_{\mathrm{p}}$ (or $\mathbf{I}_{\mathrm{g}}$) could be obtained by concatenating its associated K color LBP histograms into a single vector by column order. However, it should be noted that directly applying NN classifier to such concatenated LBP histogram vector could suffer from degradation in FR performance caused by the high dimensionality and the redundant information. To overcome the above problem, low-dimensional feature extraction techniques are adopted. Thus let us denote the i^{th} face feature extractor by $\varphi^{(i)}$.

Further, let us assume that $\varphi^{(i)}$ is formed with a training set consisting of color LBP histograms, all of which are computed from the i^{th} color component training images $\mathbf{S}^{(i)}$. Then, the low-dimensional features of $\mathbf{h}_{\text{p}}^{(i)}$ and $\mathbf{h}_{\text{g}}^{(i)}$ are obtained as follows (using the corresponding $\varphi^{(i)}$):

$$\mathbf{f}_{\text{p}}^{(i)} = \varphi^{(i)}(\mathbf{h}_{\text{p}}^{(i)}) \text{ and } \mathbf{f}_{\text{g}}^{(i)} = \varphi^{(i)}(\mathbf{h}_{\text{g}}^{(i)}), \tag{7}$$

where $\mathbf{f}_{\text{p}}^{(i)}, \mathbf{f}_{\text{g}}^{(i)} \in \Re^{D_i}$ and $i = 1, \ldots, K$.

In order to generate the proposed *color LBP features* of $\mathbf{I}_{\text{p}}$ and $\mathbf{I}_{\text{g}}$, K complementary low-dimensional features, given by (7), are combined at the level of the features (by concatenating low-dimensional features in column order):

$$\mathbf{f}_{\text{p}} = \left[\left(\mathbf{f}_{\text{p}}^{(1)}\right)^{\text{T}} \cdots \left(\mathbf{f}_{\text{p}}^{(K)}\right)^{\text{T}}\right]^{\text{T}} \text{ and } \mathbf{f}_{\text{g}} = \left[\left(\mathbf{f}_{\text{g}}^{(1)}\right)^{\text{T}} \cdots \left(\mathbf{f}_{\text{g}}^{(K)}\right)^{\text{T}}\right]^{\text{T}}, \tag{8}$$

where $\mathbf{f}_{\text{p}}, \mathbf{f}_{\text{g}} \in \Re^{D}$ and $D = \sum_{i=1}^{K} D_i$. It is important to note that, in the process of extracting color LBP features $\mathbf{f}_{\text{p}}$ and $\mathbf{f}_{\text{g}}$, $\mathbf{f}_{\text{p}}^{(i)}$ and $\mathbf{f}_{\text{g}}^{(i)}$ should be individually normalized in order to have zero mean and unit variance prior to their concatenation.

To perform FR tasks (identification or verification) on $\mathbf{I}_{\text{p}}$, a nearest neighbor (NN) classifier is then applied to determine the identity of $\mathbf{I}_{\text{p}}$ by matching $\mathbf{f}_{\text{p}}$ with the closest $\mathbf{f}_{\text{g}}$.

3. EXPERIMENTS

3.1. Experimental setup

Three publicly available face DB CMU-PIE [6], Color FERET [7], and XM2VTSDB [8] were used to evaluate the proposed color LBP feature. All facial images used in our experiments were manually cropped from original images based on the locations of the two eyes. Each cropped facial image was rescaled to the size of 112x112 pixels (see Fig. 2). As for uniform LBP operator shown in (1), we selected the $LBP_{8,2}$ operator (*i.e., P*=8 and *R*=2) as well as 18x21 pixels window for local regions [1].

In all experiments, we compared the proposed color LBP feature with both grayscale LBP feature and color feature. For FR approach using grayscale LBP features, the technique proposed in [1] was adopted; that is, only luminance information is applied for obtaining a LBP face feature. In FR approach using color features, given K different color component images, each color component vector was generated in the form of a column vector by lexicographic ordering of the pixel elements of a corresponding color component image [9]. Note that low-dimensional features of these color component vectors were combined at the level of features (in the same way as described in (8)), which results in a color feature. Also note that the parameters (related to LBP operator) used in our method were all the same as those used in FR using grayscale LBP features. This guarantees fair and stable comparisons with the proposed method. For grayscale LBP features, the "*R*" channel [9] from *RGB* color space was adopted in our experiments. On the other hand, "RQC_r" color [9] color component images (Q and C_r from *YIQ* and YC_bC_r) color spaces were used for both color LBP feature and color feature.

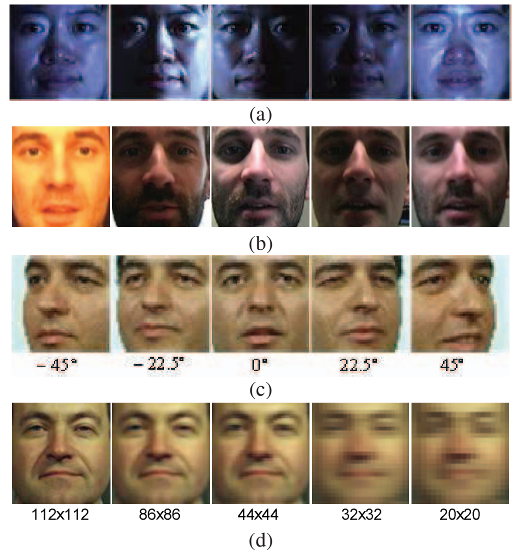

Fig. 2. (a) Examples of the facial images with flash illumination from the CMU-PIE. (b) Examples of facial images with uncontrolled illumination condition from the XM2VTSDB. (c) Examples of facial images with pose variations from the Color FERET. (d) Examples of facial images according to five different face resolutions.

Four popular low-dimensional feature extraction techniques were used: PCA, Fisher's Linear Discriminant Analysis (FLDA), Bayesian, and Regularized Linear Discriminant Analysis (RLDA). As for the NN classifiers, the Euclidean distance was used for FLDA and RLDA, while the Mahalanobis distance was used for PCA and Bayesian. In our experiments, rank-one identification rate of the cumulative match curve (CMC) [8] was used for measuring FR performance. In all experiments, the frontal-view images with neutral illumination and expression were used to build the gallery set. Moreover, the collected set of facial images was randomly partitioned into two sets: a training set and a probe set. In order to guarantee stable experimental results, 40 independent runs of aforementioned random partitions were executed. Thus, all results reported in here were averaged over 40 runs.

3.2. Experimental results

1) **Under severe illumination variation**: We evaluate the robustness of the proposed color LBP features against extensive variations in illumination using CMU-PIE and XM2VTSDB face DB. In this experiment, 1,428 frontal images of 68 subjects (21 images per subject) were collected from the CMU- PIE; the facial images for each subject have 21 different illumination variations (using the 'room lighting off' condition). From the XM2VTSDB, 1064 frontal images of 133 subjects were obtained; each subject included eight facial images captured with no control on illumination variations. Fig. 2(a) and Fig.2(b) show examples of facial images used in this experiment. By using random partition discussed above, the training set consisted of (5 images x 201 subjects), while the remaining 1,487 images were used to create a probe set. Fig. 3 shows the rank-one identification rates of color LBP, grayscale LBP, and color features. The results show that our color LBP feature outperforms both grayscale LBP and color features for all the low-dimensional feature extraction techniques

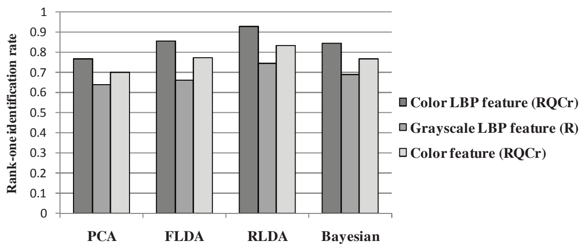

Fig. 3. Rank-one identification rates obtained for three different face features on the CMU-PIE and the XM2VTSDB.

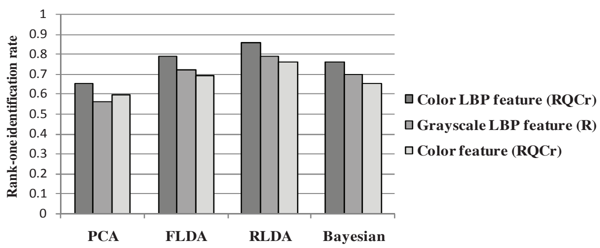

Fig. 4. Rank-one identification rates obtained for three different face features on the Color FERET.

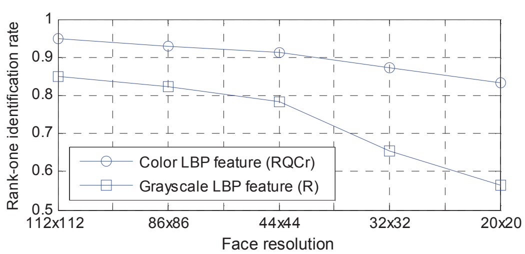

Fig. 5. Rank-one identification rates with respect to five different face resolutions of probe. Note that the RLDA is used for low-dimensional feature extraction.

considered. In particular, the color LBP feature is even more robust against illumination variations than the grayscale LBP feature, showing that the color LBP feature maintains a 12.9%, 18.2%, 15.3%, and 18.4% higher accuracy over grayscale LBP feature for PCA, FLDA, Bayesian, and RLDA, respectively.

2) **Under pose variation**: We further assess the usefulness of the color LBP feature under pose variations. A total of 1,378 face images of 107 subjects were collected from the Color FERET face DB. It should be noted that the rotated face images that both eyes can be reliably identified for normalization were only collected. The facial images used include five different pose angles ranging from –45° to +45° (see Fig. 2(c)). Also note that all the images have neutral expression and illumination. The training set consisted of (5 images x 107 subjects). The probe set contained the remaining 843 images of the same 107 subjects. The comparison results are depicted in Fig. 4. It is shown that the color LBP feature attains the highest recognition accuracies followed by the grayscale LBP and the color features. This demonstrates the effectiveness of color LBP feature on FR under pose variations.

3) **Under spatial resolution variation**: In practical applications (such as video surveillance), low-resolution face could be frequently encountered [9]. In this experiment, we further evaluate the robustness of the color LBP feature against small resolution face images. To this end, 1,428 frontal-view images of 68 subjects were selected from CMU-PIE; for one subject, facial images have 21 different lighting variations. Further, from the Color FERET, the 1,120 frontal-view images of 140 subjects (8 samples per subject) were chosen from the **fa**, **fb**, **fc**, and **dup1** sets. The training set consisted of (5 samples x 208 subjects), while the remaining 1,508 facial images for the probe set. In real-life FR applications, it is reasonable to assume that high-resolution face images are chosen as training and gallery images. On the other hand, the probe to be tested may have lower and various face resolutions [9]. Therefore, in this experiment, the face resolution of training and gallery images was fixed as 112x112 pixels, while the resolution of probe was varied as five different resolutions, as shown in Fig. 2(d). In addition, in order to match a low-resolution probe to a high-resolution gallery face, the probe has been upsampled by using a cubic interpolation technique before recognition. The experimental results of three different face features on the varying face resolutions are displayed in Fig. 5. It should be emphasized that FR accuracies for the grayscale LBP feature are highly sensitive to variations in face resolution. For example, rank-one identification rate decline from 85.2% to 56.3% as face resolution is reduced from 112x112 to 20x20 pixels. In contrast, for the case of using color LBP feature, the difference in rank-one identification rate between face resolutions of 112x112, 32x32, and 20x20 pixels are much more marginal, compared to grayscale LBP feature.

4. CONCLUSION

We examine the contribution of color to existing LBP-based texture features for improving FR performance. In this work, we exploit that the FR performance of grayscale LBP features tends to considerably degraded caused by severe changes in illumination and face resolutions. In contrast, the proposed color LBP features can achieve acceptable FR performance under these variations.

5. REFERENCES

[1] T. Ahonen, A. Hadid, and M. Pietikainen, "Face Description with Local Binary Pattern: Application to Face Recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037-2041, 2006.

[2] G. Paschos, "Perceptually Uniform Color Spaces for Color Texture Analysis: An Empirical Evaluation," *IEEE Trans. Image Processin*g, vol. 10, no. 6, pp. 932-937, 2001.

[3] A. Drimbarean and P.F. Whelan, "Experiments in colour texture analysis," *Pattern Recognit. Lett.,* vol. 22, no. 11, pp. 1161-1167, 2001.

[4] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns," *IEEE Trans. Pattern Anal. Mach. Intell*., vol. 24, no. 7, pp. 971-987, 2002.

[5] A. Jain, K. Nandakumar, and A. Ross, "Score normalization in multimodal biometric systems," *Pattern Recognit*., vol. 38, no. 12, pp. 2270-2285, 2005.

[6] T. Sim, S. Baker, and M. Bsat, "The CMU Pose, Illumination, and Expression Database," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 12, pp. 1615-1618, 2003.

[7] P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, "The FERET Evaluation Methodology for Face Recognition Algorithms," *IEEE Trans. Pattern Anal. Mach. Intell.,* vol. 22, no. 10, pp. 1090-1104, 2000.

[8] K. Messer, J. Mastas, J. Kittler, J. Luettin, and G. Maitre, "XM2VTSDB: The Extended M2VTS Database," *Proc. IEEE Int'l Conf. on AVBPA*, 1999.

[9] J. Y. Choi, Y. M. Ro, and K. N. Plataniotis, "Color Face Recognition for Degraded Face Images," *IEEE Trans. Systems, Man and Cybernetics-Part B* , vol. 39, no. 5, pp. 1217-1230, 2009.