Color Component Feature Selection in Feature-Level Fusion Based Color Face Recognition

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***Abstract*—In this paper, we propose a new color face recognition (FR) method which effectively employs feature selection algorithm in order to find the set of optimal color components (from various color models) for FR purpose. The proposed FR method is also designed to improve FR accuracy by combining the selected color components at the feature level. The effectiveness of the proposed color FR method has been successfully demonstrated using two public CMU-PIE and Color FERET face databases (DB). In our comparative experiments, traditional grayscale-based FR, previous color-based FR, and popular local binary pattern (LBP) based FR methods were compared with the proposed method. Experimental results show that our color FR method performs better than the aforementioned three different FR approaches. In particular, the proposed method can achieve 7.81% and 18.57% improvement in FR performance on the CMU-PIE and Color FERET DB, respectively, compared to representative color-based FR solutions previously developed.**

I. Introduction

Face recognition (FR) has been one of the most active research areas due to the wide range of applications including video surveillance, biometric identification, and face indexing in multimedia contents.

Recently, considerable research efforts [1-5] have been dedicated to develop color FR methods that utilize facial color information. In [1], combining spectral components across different color spaces is found to be useful for the purpose of FR. In particular, YQC_r (Y from YIQ, and Q and C_r from YIQ and YC_bC_r, respectively) color configuration shows better FR performance than other color configurations. In [2], a new color representation, the so-called the Independent Color Space (*ICS*), for FR purpose is proposed. The author shows that *ICS* color representation is effective for enhancing the FR performance, compared to the use of color images represented in the *RGB* color space. In [3], an optimal conversion of *RGB* color images into a monochromatic form is proposed using a color image discriminant model. In [4], integrating color components of a particular color space into the boosting framework achieves improved FR performance, compared to grayscale based FR. In our previous work [5], the fusion of facial color information at the input level can improve FR performance by at least an order of magnitude over grayscale features when low-resolution faces (e.g., 25 x 25 pixels or less) are applied to FR system.

Most color FR methods developed so far (including our previous work) are restricted to using only two or three color components that are *heuristically* selected from predetermined color spaces [1], [3]-[5]. The FR performance of such heuristic-based solutions could be degraded under different FR operating conditions, such as illumination and pose variations. The underlying reason for this is that different color models may have different characteristics and effectiveness in the view point of features for classification [6]. Hence, in FR methods relying on color information, one important problem is to optimally determine a set of color components from various color models, aiming to attain the best FR performance.

In this paper, we propose new color FR method to overcome the limitations of the previous color FR methods. The proposed method employs both feature selection and feature-level fusion classification techniques. The proposed method has the following two distinct characteristics:

1) The proposed method seeks to find the optimal set of color components from available color spaces using feature selection algorithm, aiming to achieve the best FR performance. We employ feature selection where color components are considered as features in classification. To the best of our knowledge, our work is the first attempt to incorporate feature selection scheme into FR techniques using color information.
2) To effectively take a complement effect from the selected color components, the individual features extracted from them are combined at the feature level. Due to the dimensionality reduction by feature extraction process, we can avoid the degradation of FR performance arising from the curse of dimensionality. The resulting combined feature vector is used for FR tasks (i.e., subject identification or verification).

The rest of the paper is organized as follows. In Section 2, we explain the proposed color FR method in detail. In Section 3, we present experimental results to demonstrate the effectiveness of the proposed color FR method. Conclusions and direction for future research are presented in Section 4.

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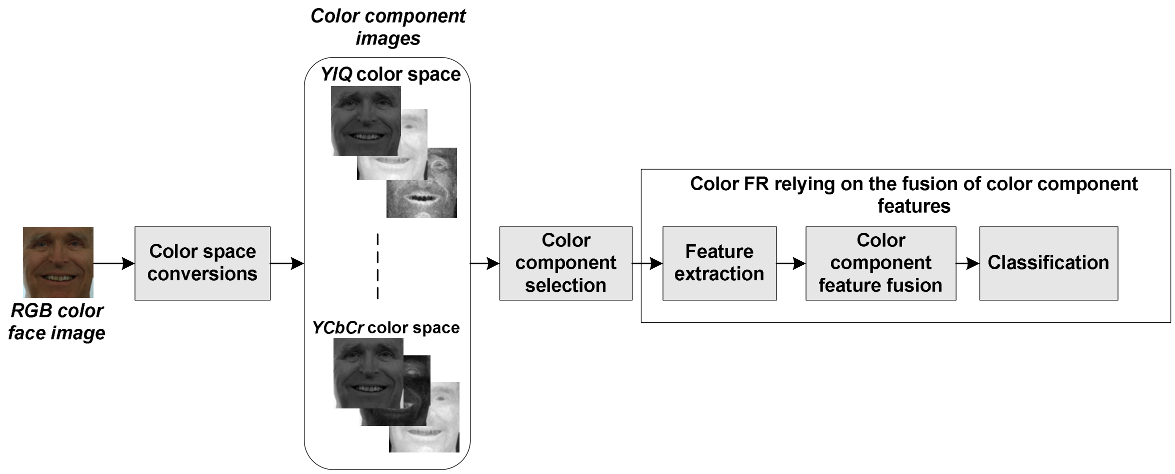


Fig. 1. Overview of the proposed color FR framework.

II. The Proposed Color FR Method

In this section, we describe the proposed color FR method based on feature selection algorithms and FR based on feature information fusion. Fig. 1 provides an overview of the proposed color FR framework. As shown in Fig. 1, red-green-blue (RGB) color face images are first converted into a number of different color spaces. Let us assume that a total of M different color component images are generated. Let $\mathbf{s}_m$ be the m^{th} color component vector which is a column vector by lexicographic ordering of the pixel elements of a 2-D color component image.

Let $\mathbf{S} = \{\mathrm{s}_m\}_{m=1}^{M}$ be the set of color component vectors (s_m), with cardinality M. Let M' denotes the number of color component vectors in the selected subset $\mathbf{S}'$, *e.g.,* $\mathbf{S}' \subseteq \mathbf{S}$. The color component selection problem is interpreted as finding a subset $\mathbf{S}'$ which optimizes an evaluation measure denoted by $J(\mathbf{S}')$. The task of $J(\mathbf{S}')$ is to evaluate the goodness (or relevance) of a subset $\mathbf{S}'$ for classification purpose, where $J : \mathbf{S}' \subseteq \mathbf{S} \rightarrow \Re$. Detailed descriptions for $J(\mathbf{S}')$ and feature information fusion for FR are given in the following subsections.

A. Feature Selection for Color Component Set

In this section, we discuss the details of color component selection. In a typical classification system, feature selection algorithms and evaluating features are key components. In this paper, we focus on describing the evaluation measure $J(\cdot)$ which is a cost function for the feature selection. It should be noted that any feature selection algorithm can be applied in the proposed color FR framework. In this paper, we adopt sequential floating forward search (SFFS) as a feature selection algorithm [9]. In our color FR method, Bayesian probability of error (BPE) is adopted to evaluate the goodness of selected color components. Since the classification process of a typical FR is usually done using distance-based nearest neighbor (NN) classifiers [2], [5], we derive BPE by using the distances computed in feature space. We now develop BPE in the context of FR framework. Let $\Omega = \{\omega_1, \omega_2, \ldots \omega_G\}$ be a set of G classes (i.e., subjects) to be recognized. Also let $\{\mathbf{I}_{\mathrm{t}}^{(i)}\}_{i=1}^{N_t}$ be the testing set of N_{t} unlabelled RGB color face images $\mathbf{I}_{\mathrm{t}}^{(i)}$. Given $\mathbf{S}'$, which is generated from a feature selection algorithm, we denote the face feature (refer to (6) for the detailed definition) by $\mathbf{f}_{\mathrm{t}}^{(i)}$. Then an NN classifier is assumed to output the distance score ($d_{i,j}$) between $\mathbf{f}_{\mathrm{t}}^{(i)}$ and a gallery face feature (produced in the same manner) of the j^{th} class.

To represent BPE in the form of posterior probability, a distance $d_{i,j}$ needs to be converted into the corresponding confidence value. Here, the confidence value represents the belief (or likelihood) that the identity label of the j^{th} class is assigned to that of i^{th} face feature. Using a sigmoid function, the confidence value of $d_{i,j}$ is computed as follows:

$$c_{i,j} = 2 \cdot \frac{1}{1+\exp(d_{i,j})}, \tag{1}$$

where $1 \le i \le N_t$ and $1 \le j \le G$. It should be noted that $d_{i,j}$ must be normalized to have zero mean and unit standard deviation prior to the computation of $c_{i,j}$. A detailed description for normalization techniques can be found in [10]. In sequence, a sum normalization method [10] is used to approximate the posterior probability defined as follows:

$$P(\omega_k \mid \mathbf{f}_{\mathrm{t}}^{(i)}) = \frac{c_{i,k}}{\sum_{j=1}^{G} c_{i,j}}. \tag{2}$$

In (2), $P(\omega_k \mid \mathbf{f}_{\mathrm{t}}^{(i)})$ represents the probability that the identity label of $\mathbf{f}_{\mathrm{t}}^{(i)}$ is equal to that of the class ω_k. Using (2), as an evaluation measure, BPE as a function of $\mathbf{S}'$ is defined as follows:

$$J(\mathbf{S}') = \sum_{i=1}^{N_t}\left(1 - \max_k P(\omega_k \mid \mathbf{f}_t^{(i)})\right). \tag{3}$$

Finally, optimal color component set ($\mathbf{S}_{\text{opt}}$) is determined by finding the $\mathbf{S}'$ which minimizes $J(\mathbf{S}')$, i.e.,:

$$\mathbf{S}_{\text{opt}} = \arg\min_{\mathbf{S}'} J(\mathbf{S}'), \quad \forall \mathbf{S}' \subseteq \mathbf{S}. \tag{4}$$

The color components contained in $\mathbf{S}_{\text{opt}}$ are cast into the color FR based on feature information fusion, which is explained in the following subsection.

B. Color FR Using Color Component-feature Fusion

In this section, we explain the color FR method using an optimal color component set (i.e., $\mathbf{S}_{\text{opt}}$) determined based on the feature selection discussed in Section 2.1. Recall that M' selected color components are included in $\mathbf{S}_{\text{opt}}$. Then, given $\mathbf{S}_{\text{opt}}$, the M' selected color components are separately applied to construct M' corresponding feature extractors – resulting in M' different (or individual) feature extractors. We denote the k^{th} feature extractor by $\varphi_k(\cdot)$ that is formed with a training set of the k^{th} color component vectors in $\mathbf{S}_{\text{opt}}$. Note that any existing face feature extraction techniques (such as Principal Component Analysis (PCA)) can be incorporated into the proposed color FR method.

Let $\{\mathbf{I}_g^{(n)}\}_{n=1}^{G}$ be the gallery set of G enrolled *RGB* color face images of known individuals, containing G different subjects to be identified. Also we denote the k^{th} color component vectors of $\mathbf{I}_g^{(n)}$ and $\mathbf{I}_t^{(m)}$ by $\mathbf{s}_g^{(n,k)}$ and $\mathbf{s}_t^{(m,k)}$, respectively. Note that $\mathbf{s}_g^{(n,k)}, \mathbf{s}_t^{(m,k)} \in \mathbf{S}_{\text{opt}}$. In order to obtain the color component features of $\mathbf{s}_g^{(n,k)}$ and $\mathbf{s}_t^{(m,k)}$, individual $\varphi_k(\cdot)$ is separately used in the following way:

$$\mathbf{f}_g^{(n,k)} = \varphi_k(\mathbf{s}_g^{(n,k)}) \text{ and } \mathbf{f}_t^{(m,k)} = \varphi_k(\mathbf{s}_t^{(m,k)}), \tag{5}$$

where $\mathbf{f}_g^{(n,k)}, \mathbf{f}_t^{(m,k)} \in \Re^{F_k}$ and $1 \le k \le M'$.

To generate the face features of $\mathbf{I}_g^{(n)}$ and $\mathbf{I}_t^{(m)}$, M' color component features are combined (or fused) at the feature-level by concatenating them in column order:

$$\begin{aligned}\mathbf{f}_g^{(n)} &= \left[(\mathbf{f}_g^{(n,1)})^{\mathrm{T}} \quad (\mathbf{f}_g^{(n,2)})^{\mathrm{T}} \quad \cdots \quad (\mathbf{f}_g^{(n,M')})^{\mathrm{T}}\right]^{\mathrm{T}} \text{ and} \\ \mathbf{f}_t^{(m)} &= \left[(\mathbf{f}_t^{(m,1)})^{\mathrm{T}} \quad (\mathbf{f}_t^{(m,2)})^{\mathrm{T}} \quad \cdots \quad (\mathbf{f}_t^{(m,M')})^{\mathrm{T}}\right]^{\mathrm{T}},\end{aligned} \tag{6}$$

where T denotes the transpose operator of the matrix, $\mathbf{f}_g^{(n)}, \mathbf{f}_t^{(m)} \in \Re^F$, and $F = \sum_{k=1}^{M'} F_k$. Note that both $\mathbf{f}_g^{(n,k)}$ and $\mathbf{f}_t^{(m,k)}$ should be individually normalized to have zero mean and unit variance prior to their combination.

In order to perform FR tasks (identification or verification), an NN classifier in the classification module shown in Fig. 1 is applied to determine the identity of $\mathbf{I}_t^{(m)}$ as follows:

$$l(\mathbf{I}_t^{(m)}) = l(\mathbf{I}_g^{(n^*)}) \text{ and } n^* = \arg\min_n \chi(\mathbf{f}_t^{(m)}, \mathbf{f}_g^{(n)}), \tag{7}$$

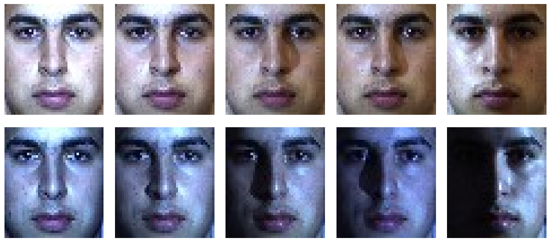
where $l(\cdot)$ returns the identity label of a face image and $\chi(\cdot)$ denotes the distance metric.

III. Experiments

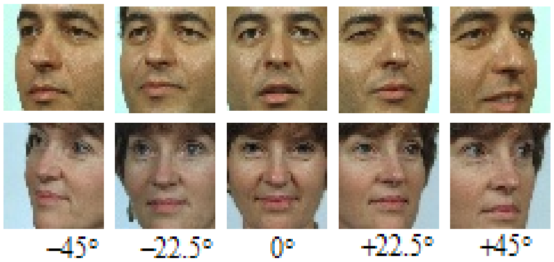
A. Experimental Setup and Conditions

In order to evaluate the effectiveness of proposed color FR method in terms of FR performance, two de facto standard data sets of the CMU-PIE [7] and the Color FERET face DB [11] were used in our experiments. From the CMU-PIE, a total of 2,856 frontal-view face images with neutral expression were chosen to form an experimental dataset. For one subject, 42 face images have 42 different illumination variations with 'room lighting on' and 'room lighting off' conditions. From the Color FERET, a total of 972 face images (12 images per one subject) of 81 subjects were collected for our experiments. All these images include five different pose variations. Specifically, the pose angles are range from –45° to +45° as shown in Fig. 2(b). Fig. 2 shows some examples of facial images used in our experiments. Note that the face images shown in Fig. 2 were rotated and rescaled to 44 x 44 pixels according to recommendation of the standard FERET protocol.

To perform color component selection process described in Section 2.1, the following eight different color spaces were used: *YC$_b$C$_r$, YIQ, HSV, JPEG-XR* (*Co, Cg* and *Y*)*, RGB, YUV, XYZ, L*a*b**. We applied a total of 24 distinct color components, derived from eight different color spaces, to the feature selection process. The *YIQ* color space defined in the National Television System Committee (NTSC) video standard was adopted. The *YC$_b$C$_r$* color space is scaled and is the offset version of the *YUV* color space. In addition, *JPEG-XR* [8] is designed for still-image coding algorithm and file format for continuous-tone photographic images developed by Microsoft. Note that the definitions of the corresponding luminance components (*Y*) from five color spaces (*YC$_b$C$_r$, YIQ, JPEG-XR, YUV* and *XYZ*) are different from each other. The further detailed descriptions for the color spaces used can be found in [6]. Note that feature selection is typically carried out in an off-line manner. Hence, the separate validation set from the testing set used during actual FR operation needs to be constructed for the process of selecting

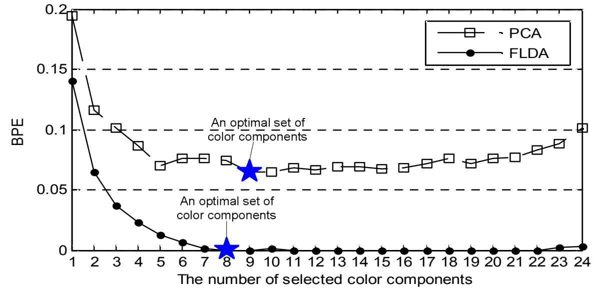


(a)

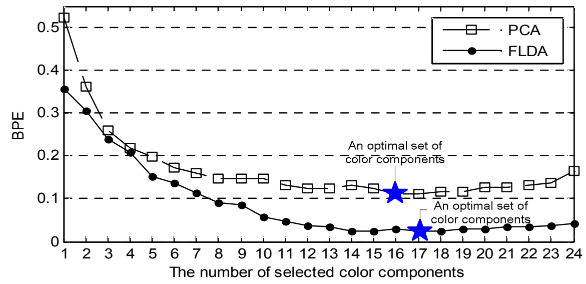


(b)

Fig. 2. Examples of facial images used in our experiments. (a) Examples of face images from the CMU-PIE. The face images in the first row have illumination variations with 'room lighting on', while those in the second row have illumination variations with 'room lighting off'. (b) Examples of face images from the Color FERET. Each pose angle is represented below a corresponding face image. Note that all facial images are manually cropped using eye coordinate information.



(a)



(b)

Fig. 3. The BPE curves obtained for PCA and FLDA as a function of the number of selected color components. It should be noted that the validation set is used to compute BPE in the process of selecting color components. (a) CMU-PIE. (b) FERET.

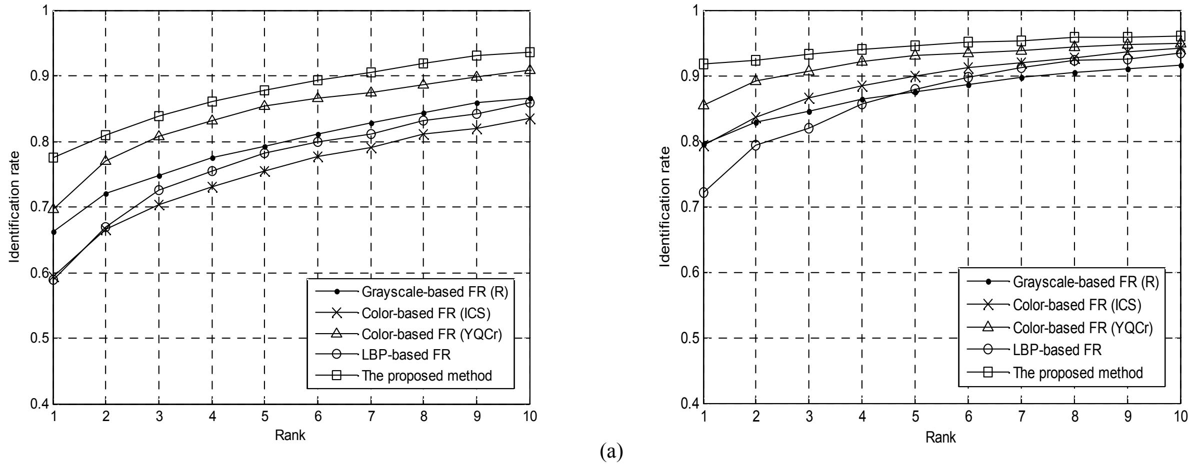
optimal color components. For this purpose, each set consisting of collected face images in CMU-PIE or Color FERET was randomly partitioned into three subsets: training, validation, and testing sets. For the case of CMU-PIE, the training set consisted of (5 samples x 68 subjects) face images, while validation set was composed of (15 samples x 68 subjects). Also, the remaining 1,496 face images (22 samples per subject) were used to create a testing set. For the case of Color FERET, using random partition, the training set consisted of (3 samples x 81 subjects) face images, while validation set was composed of (3 samples x 81 subjects), and the remaining 486 face images (6 samples per subject) were used to construct a testing set. Note that, for CMU-PIE, we constructed a gallery set composed of 68 different samples corresponding to 68 different subjects to be identified. Note that, for Color FERET, a gallery set comprised of 81 different samples corresponding to 81 different subjects. Gallery images had neutral illumination and expression according to the standard regulations for gallery registration described in [11].

As for feature selection algorithm, we adopted Sequential Floating Forward Search (SFFS) [9]. It is widely accepted that SFFS outperforms the other feature selection algorithms, considering both classification performance and execution time. In our experiments, PCA and Fisher's Linear Discriminant Analysis (FLDA) face feature extraction technique were used to create $\varphi_k(\cdot)$ shown in (5). The PCA and FLDA have been widely used as a benchmark for evaluating and comparing FR performance. To perform NN-based classification, Euclidean distance was used for both PCA and FLDA.

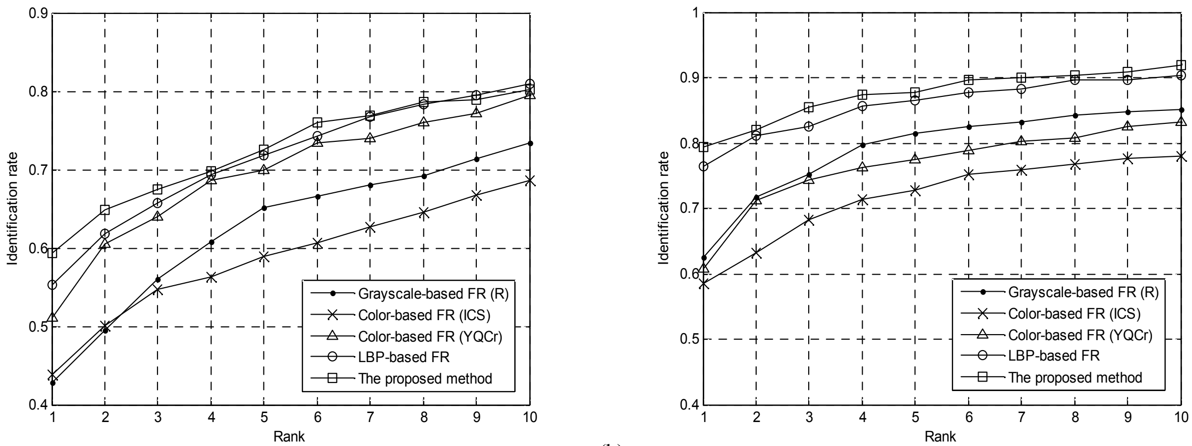
B. Experimental Results

The first experiment has been carried out by applying SFFS method to 24 color component data set in order to calculate BPE, given by (3). The resulting BPE curves are shown in Fig. 3. In Fig. 3, as more features are added, BPEs decrease for both PCA and FLDA, which then achieve minimum BPE (at the optimal number of 8 or 9 features for CMU-PIE and 16 or 17 for Color FERET, respectively), and eventually increase again. These results demonstrate that the optimal number of color components (as well as the types of color components) for classification purpose could be changed with different FR conditions (e.g., illumination or pose variations). Using feature selection method, the results in Fig. 3 show that we can find the optimal set of color components in the sense of minimizing BPE given by (3).

The second experiment has been designed to assess the performance of the proposed color FR method using the optimal set of color components resulting from SFFS. For comparison purpose, FR performances of grayscale-based FR, previous color-based FR [1]-[2], and Local Binary Pattern (LBP) [12] based FR techniques are presented. For grayscale-based FR method, the FR performances obtained using R grayscale [5] (from RGB color space), while, for previous color-based FR methods, independent Color Space (ICS) [2], and YQC_r (Y and C_r from YC_bC_r and Q from YIQ) [1] color components were used. It should be noted that, in previous color FR methods, the approach to make use of three pre-specified color components is exactly the same as that used in the proposed method. In other words, three low-dimensional face features, each of which is obtained from



(a)



(b)

Fig. 4. Comparisons of identification rates between the proposed color FR method and the other FR techniques. The figures on the left-hand side are for PCA, while those in the right-hand side are for FLDA. Note that testing set was used to measure the FR performance and the optimal set of color components determined using SFFS feature selection algorithm were applied to the proposed method. (a) CMU- PIE. (b) FERET.

a corresponding color component vector, are combined at the level of features. This guarantees fair and stable comparisons with the proposed method. The recently proposed LBP features are originally designed for texture description. In [12], LBP achieves a better FR performance than Eigenface, Bayesian, and EBGM methods. Note that, here, the $\mathrm{LBP}_{8,2}^{u_2}$ operator was selected, using 18x21 pixel windows and the Chi square statistic χ^2 as distance metric. Further, for computing the weighted χ^2 statistic, the local region weights proposed in [12] were employed. Further details regarding the parameters used by LBP-based baseline FR can be found in [12]. In order to guarantee stable experimental results, 20 runs of random partition were repeated 20 times and therefore all of the results reported here were averaged over 20 times.

Fig. 4 shows the comparisons of the FR accuracies of the proposed color FR with the other four aforementioned FR approaches. In LBP-based FR, *R* grayscale is used for texture analysis. In Fig. 4, the horizontal axis denotes the rank, where rank *k* indicates the probability that the gallery image from the correct individual is among the top *k* matches to a probe, and the vertical axis represents the correct identification rate.

As can be seen in Fig. 4, for both CMU-PIE and Color FERET DB, the proposed method performs better than the other four FR approaches. Specifically, for the case of using CMU-PIE (see Fig. 4(a)), the proposed method can attain 11.28%, 18.16%, 7.81% and 18.62% improvement in rank-one identification rate for PCA, compared to grayscale-based FR, two color-based FR (*ICS* and YQC_r), and LBP-based FR methods, respectively. For FLDA, the enhancements of 12.36%, 12.49%, 6.48% and 19.63% can be achieved in comparison to the other four FR methods in the same order as PCA. In addition, it is shown that LBP-based FR method shows the worst FR performance against severe illumination variation. This result is consistent to previous reports that LBP representation is sensitive to non-monotonic illumination changes [13]. On the other hand, the proposed color FR method is found to be highly robust to extensive variations in illumination.

For the case of using Color FERET, the proposed method can maintain 16.43%, 15.52%, 8.15% and 3.97% improvement in rank-one identification rate, compared to the other four FR approaches in the same order as the case of using CMU-PIE. For FLDA, the improvements of 16.86%, 20.86%, 18.57% and 3.01% can be achieved by the proposed method. This demonstrates the effectiveness of the proposed color FR method on face recognition under pose variations.

IV. Conclusion and Discussion

In this paper, we propose new color face recognition (FR) method which makes effective use of feature selection to find the set of optimal color components from various color models. The experimental results show that the proposed method significantly improve the FR performance of other existing FR methods in both face databases used (CMU-PIE including illumination variations and Color FERET including pose variations).

For future work, we will further advance the proposed color FR method by incorporating *weighting techniques* into our method. The weighting technique (to be incorporated) will be based on an adaptive fuzzy technique describe in [6]. In an adaptive fuzzy technique, a fuzzy averaging operation is performed in order to replace the noisy vector at the window center with a suitable representative vector. The general form of the adaptive fuzzy system proposed is given as a *fuzzy weighted average* of the input vectors inside the window, estimating the uncorrupted multivariate image signal by determining the centroid of the input set. This method effectively reduces the level of random noise present in the signal, while all the vectors inside the window contribute to the final filtered output.

Motivated by the adaptive fuzzy technique discussed above, we will apply a weighting technique (associated with color component features) to the proposed color FR method. More specifically, different weights are assigned to the feature vectors of the selected color components aiming to improve FR performance. The weight of each color component feature is determined using the degree to which the color component contributes to the improvement in FR performance. For instance, given a particular FR environment (or condition), we can assess the separate FR performance using each color component that is selected by feature selection process. Hence, we can impose higher weight on the color component showing high FR performance, while lower weight on the color component showing low FR performance. Through using the weighted fusion of color component features, we will also demonstrate the usefulness of color component selection for improving FR performance under much more challenging FR conditions, such as resolution variations or occlusion problems.

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