Color Based Fisher Discriminative Analysis Features for Face Recognition

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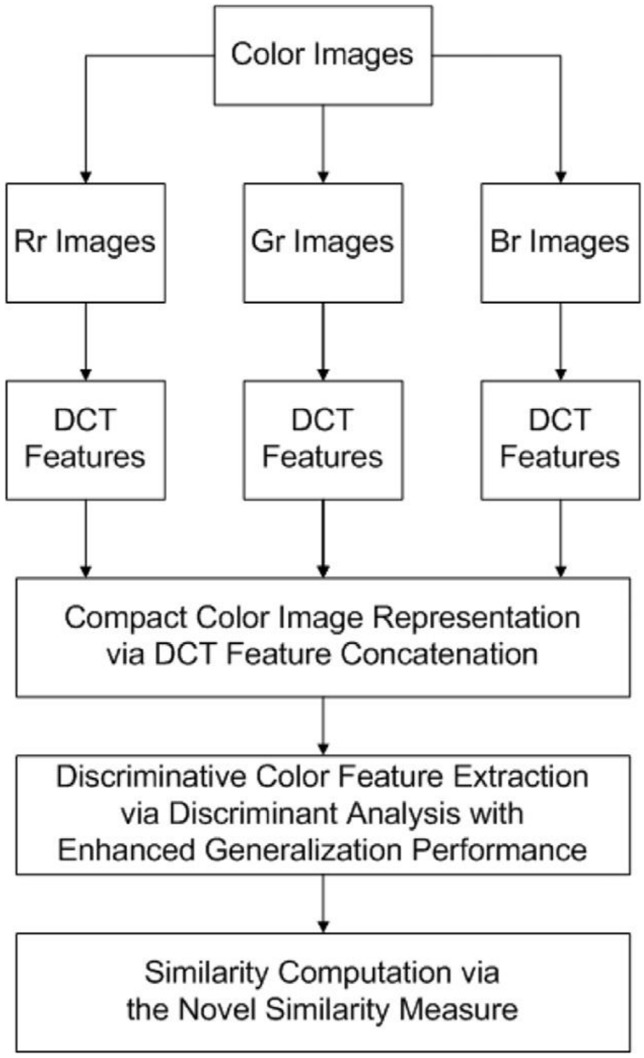
Abstract- *This paper presents a discriminative color features (DCF) method, which applies a simple yet effective color model, a novel similarity measure, and effective color feature extraction methods, for improving face recognition performance. First, the new color model is constructed according to the principle of Ockham's razor from a number of available models that take advantage of the subtraction of the primary colors for boosting pattern recognition performance. Second, the novel similarity measure integrates both the angular and the distance information for improving upon the broadly applied similarity measures. Finally, the discriminative color features are extracted from a compact color image representation by means of discriminant analysis with enhanced generalization capabilities. Experiments on the Face Recognition Grand Challenge (FRGC) version 2 Experiment 4, which contains 12,776 training images, 16,028 controlled target images, and 8,014 uncontrolled query images, show the feasibility of the proposed method.*

Keywords- Fishers discriminate analysis, and Euclidean distance measure

I. INTRODUCTION

Modern research in design recognition uncovers that distinctive shading models have diverse discriminative power (Jones and Abbott, 2004; Shih and Liu, 2005; Neagoe, 2006; Liu, 2008b; Liu and Yang, 2009). Contrasted with the grayscale images, shading images have considerably more data helpful for enhancing face recognition execution (Shih and Liu, 2005; Liu and Yang, 2009). To misuse the essential shading data, novel and successful transforms from the RGB shading space have been explored for improving confront recognition execution. Jones and Abbott (2004) propose a transform of shading images to monochromatic images utilizing the Karhunen– Loeve (KL) transform, direct relapse, and hereditary calculations for enhancing human face recognition upon the grayscale images. Negate (2006) presents an ideal 2D shading space transform utilizing the KL transforms for confront recognition. Liu (2008b)

Demonstrates that the Uncorrelated Color Space (UCS), the Independent Shading Space (ICS), and the Discriminating Color Space (DCS) can enhance confront recognition execution. The inspiration of this paper is three-overlay. Initial, another shading display is developed by applying the subtraction of the essential hues for boosting design recognition execution. For shading image portrayal, the tri-jolt hypothesis of shading recognition states that any shading can be spoken to well by the blend of three essential hues: the red, the green, and the blue hues. For shading image characterization, in any case, the shading models that contain the weighted subtraction of the essential hues have been appeared more powerful than the shading spaces characterized by the essential hues. Cases of these more powerful shading models incorporate the KL shading spaces (Jones and Abbott, 2004; Neagoe, 2006), the UCS, the ICS, the DCS (Liu, 2008b; Liu and Yang, 2009), where the shading segment images include the weighted subtraction of the essential hues. As the quantity of the conceivable shading models that contain the weighted subtraction of the essential hues can achieve vastness, we apply the guideline of Ockham's razor (Russell and Norvig, 2010) to characterize one straightforward yet powerful shading model for enhancing face recognition execution. Second, a novel likeness measure is displayed to move forward upon the famous similitude measures, for example, the Euclidean separation measure (Liu and Wechsler, 2000a,b), the L1 remove measure (Liu and Wechsler, 2002), the Mahalanobis remove measure (Liu and Wechsler, 2001), the cosine likeness measure (Liu, 2006), the brighten cosine likeness measure (Phillips et al., 2005; Liu, 2006), and the standardized relationship measure (Kittler et al., 2000; Struc and Pavesic, 2008), for enhancing face recognition execution. Indeed, similitude measures can altogether influence the execution of an example recognition framework, and unique closeness measures ought to be connected for various component extraction techniques (Liu, 2007, 2008a). The Euclidean separation measure, for instance, is broadly connected in numerous neural system models and bolsters vector machines (Haykin, 1999; Vapnik, 1999), and the L1 separate and the Mahalanobis remove measures are viable for the PCA-based component extraction techniques (Liu and Wechsler, 2001, 2002). The brighten cosine comparability measure has been shown viable for a huge scale confront recognition issue while applying the eigenfaces strategy (Phillips et al., 2005), arrangement execution when joined with the discriminant analysis technique (Liu, 2006). The cosine comparability and the standardized relationship measures, in any case, consider just the casual data and totally disregard the separation data between the objective and inquiry design vectors. To beat the inadequacies of these prominent comparability measures, we show another similitude measure that incorporates both the precise and the separation data for enhancing face acknowledgment execution. At long last, the discriminative shading highlights are extricated from a conservative shading picture portrayal by methods for discriminant investigation with improved speculation capacities. We examine in this paper new discriminative shading highlights got from a basic (for enhanced computational proficiency) yet viable (for moved forward confront acknowledgment execution) shading model, as various errands require diverse shading models. To determine the new discriminative shading highlights, the dimensionality of each shading part picture of the new shading model is decreased utilizing the Discrete Cosine Transform (DCT), and the DCT highlights removed from all the three segment pictures are connected to frame an increased example vector. The enlarged example vector is additionally handled by discriminant analysis for compelling element extraction. Discriminant analysis, which separates includes that are best for class distinguishableness, is executed by methods for synchronous diagonalization to encourage improved speculation. Fig. 1 demonstrates the framework design of the discriminative shading highlights (DCF) strategy. The adequacy of the proposed technique is evaluated utilizing a extensive scale, terrific test issue, to be specific, the Face Recognition Amazing Challenge (FRGC) issue (Phillips et al., 2005). The test originates from extensive enlightenment varieties, low picture quality of the inquiry pictures thought about against the objective pictures, movement obscuring, picture commotion, and so forth.. The FRGC gauge calculation demonstrates that it can accomplish under 12% face check rate at 0.1% false acknowledge rate. Exploratory outcomes likewise uncover that our new shading model is more viable than the RGB shading space, the HSV shading space, the Lab shading space, the grayscale pictures, and our proposed new similitude measure performs superior to the prevalent Euclidean separation measure, the cosine likeness measure, and the standardized relationship measure.



II. FISHER'S DISCRIMINATIVE ANALYSIS

The augmented pattern vector, which contains the compact information of the R, G, Br image, is further processed to extract the discriminative colour features for face recognition. One popular feature extraction method is discriminant analysis, which optimizes the criteria of class separability based on scatter matrices. Discriminant analysis, however, often displays poor generalization performance due to over fitting. To analyze how over fitting occurs in discriminant analysis and how to overcome it to enhance its generalization capabilities, we now briefly review the simultaneous diagonalization of the within-class and between-class scatter matrices,

In the case where there are more than two classes, the analysis used in the derivation of the Fisher discriminant can be extended to find a subspace which appears to contain all of the class variability. Suppose that each of C classes has a mean μ_i and the same covariance Σ. Then the between class variability may be defined by the sample covariance of the class means

$$\Sigma_b = \frac{1}{C}\sum_{i=1}^{C}(\mu_i - \mu)(\mu_i - \mu)^T$$

where μ is the mean of the class means. The class separation in a direction $\vec{w}$ in this case will be given by

$$S = \frac{\vec{w}^T \Sigma_b \vec{w}}{\vec{w}\Sigma\vec{w}} = \frac{\vec{w}^T (\Sigma_b \Sigma^{-1}) \Sigma \vec{w}}{\vec{w}\Sigma\vec{w}}$$

This means that when $\vec{w}$ is an eigenvector of $\Sigma_b\Sigma^{-1}$ the separation will be equal to the corresponding eigenvalue. Since Σ_b is of most rank C-1, then these non-zero eigenvectors identify a vector subspace containing the variability between features. These vectors are primarily used in feature reduction, as in PCA. The smaller eigenvectors will tend to be very sensitive to the exact choice of training data, and it is often necessary to use as described in the next section. Other generalizations of LDA for multiple classes have been defined to address the more general problem of distributions (i.e., where the data distributions are not homoscedastic). One such method is LDA (see e.g. HLDA among others). If classification is required, instead of dimension reduction, there are a number of alternative techniques available. For instance, the classes may be partitioned, and a standard Fisher discriminant or LDA used to classify each partition. A common example of this is "one against the rest" where the points from one class are put in one group, and everything else in the other, and then LDA applied. This will result in C classifiers, whose results are combined. Another common method is pairwise classification, where a new classifier is created for each pair of classes (giving C(C-1) classifiers in total), with the individual classifiers combined to produce a final classification.

Fisher's discriminant method is as follows:

Find the vector $\hat{a}$ maximizing the separation function $|S(a)|$,

$$S(a) = \frac{\bar{Y}_1 - \bar{Y}_2}{S_Y},$$

where

$$\bar{Y}_1 = \frac{\sum_{i=1}^{n_1} Y_i}{n_1}, \bar{Y}_2 = \frac{\sum_{i=n_1+1}^{n_1+n_2} Y_i}{n_2}, S_Y^2 = \frac{\sum_{i=1}^{n_1}(Y_i - \bar{Y}_1)^2 + \sum_{i=n_1+1}^{n_1+n_2}(Y_i - \bar{Y}_2)^2}{n_1 + n_2 - 2},$$

and

$$Y_i = a^t X_i, i = 1, 2, \ldots, n_1 + n_2$$

the nearness of the watermark, the first KLT transform grid (i.e. the one processed from the unique image) is required. After the coefficients' extraction, a relationship with the watermark arrangement is finished. A few other methods for utilizing the coefficients and the keys are expressed as could reasonably be expected, be that as it may, none is expressly clarified. In the trial area, the recommended watermarked plot is tried just against three sorts of assaults, i.e. low-pass separating, re-scaling and JPEG pressure.

III. EXPERIMENTAL RESULTS

This area surveys the adequacy of our proposed discriminative shading highlights (DCF) technique utilizing an extensive scale, stupendous test confront acknowledgment issue, specifically, the Face Recognition Great Challenge (FRGC) issue. Specifically, we first quickly clarify the FRGC variant 2 database, the most difficult FRGC Examination 4, and the FRGC benchmark calculation. We at that point evaluate our proposed DCF technique utilizing the most difficult FRGC adaptation 2 Experiment 4, and assess distinctive likeness measures, for example, the Euclidean separation measure, the cosine likeness measure, the standardized connection measure, our new closeness measure with L2 standard, and our new closeness measure with L3 standard, separately. We at long last analyze the face acknowledgment executionrespectively. We finally compare the face recognition performancewatermarking technique proposed in this paper is a plan that uses an important mystery image IK, of size M × M as the watermarking key. The first image to be watermarked, of size R × R, will be called Io in the accompanying. For effortlessness of documentation, we consider square images, yet the strategy can be inconsequentially stretched out to rectangular images. From the watermarking key IK the accompanying are registered: an arrangement of KLT eigenvectors (premise images) to be utilized as a part of the watermarking process; a watermark which is an i.i.d. Gaussian grouping s, i.e. a Gaussian circulation with invalid mean and standard deviation equivalent to σ2 s . The arbitrary esteems are registered introducing a pseudo-irregular generator with a seed gotten from the KLT premise images of IK. These two stages are talked about in the accompanying subsection that presents the age of the data that is univocally and covertly connected with the proprietor of the watermark. To register an arrangement of eigenvectors of IK, the three shading segments RGB of the image are considered. The pixels make up an irregular field of vectors of size 1 × 3, thus the KLT of the shading segments is registered. Give us a chance to call the three eigenvectors e1, e2 and e3. Duplicating the focused (i.e. with zero mean) pixels of a image by this orthonormal premise will deliver three channels; for instance, (x, y) is a segment vector speaking to a focused pixel estimation of directions (x, y) at that point pixels of the main channel can be processed as takes after: (x, y). Note that in this first exemplification we utilize this transform to figure the eigenvectors of IK. This sort of transform has likewise been utilized as a part of the pressure field, to assemble a distinguishable KLT [21]. In any case, different eigenvectors registered with marginally extraordinary techniques are conceivable: these strategies recommend a future research bearing for us. The new three channels of size M×M, which we call L1, L2 andL3, are viewed as separately. At the present time, onlyL1 is utilized for the watermark addition, on the grounds that for the most part it contains the biggest measure of vitality display in the image. In this manner, it is less delicate to assaults to the watermark, since harming this channel would to a great extent debase the subsequent image. The image L1 is then isolated into an arrangement of b × b non-overlapping sub-images of size n × n, where b = M/n.

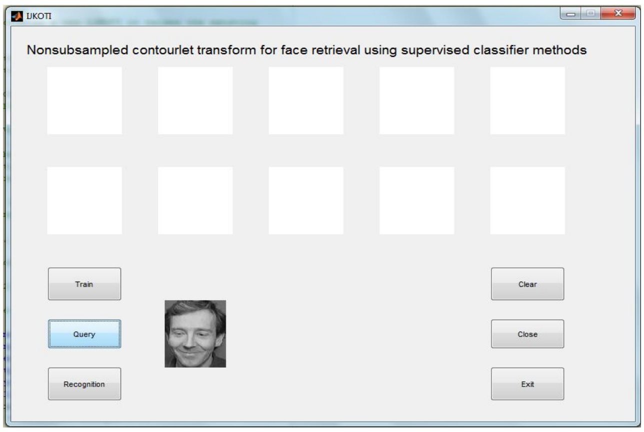


Figure 1: Test image

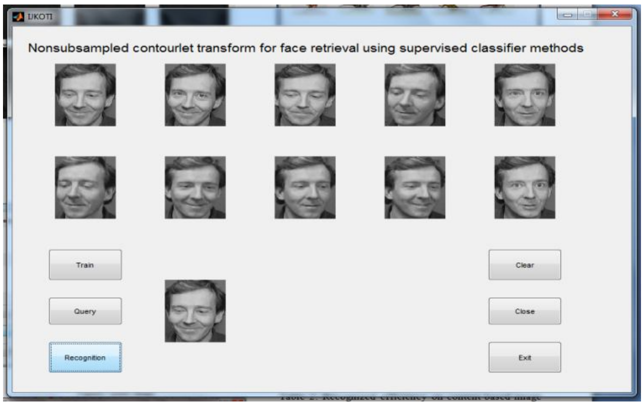


Figure 2: Retrieval images

Methods	Number of top matches				
	1	3	5	7	10
Mean value	100	77.5	71	65	58
Variance	100	58.5	50.5	44.2	36.25
Diagonal (SVD)	100	60	54.5	48.2	42.25
Fisher's analysis	**100**	**91**	**87**	**81.35**	**71.5**

Table1: Face recognition comparisons

IV. CONCLUSIONS

This paper presents a discriminative color features (method, which applies a simple yet effective color model, a novel similarity measure, and effective color feature extraction methods, for improving face recognition performance. First, the new color model is constructed according to the principle of Ockham's razor from a number of available models that take advantage of the subtraction of the primary colors for boosting pattern recognition performance. Second, the novel similarity measure integrates both the angular and the distance information for improving upon the broadly applied similarity measures. Finally, the discriminative color features are extracted from a compact color image representation by means of discriminant analysis with enhanced generalization capabilities. Experiments on the Face Recognition Grand Challenge (FRGC) version 2 Experiment 4, which contains 12,776 training images, 16,028 controlled target images, and 8,014 uncontrolled query images, show the feasibility of the proposed method.

REFERENCES

[1] M. Vetterli and J. Kovaˇcevi´c, Wavelets and Subband Coding.Prentice- Hall, 1995.

[2] S. Mallat, A Wavelet Tour of Signal Processing, 2nd ed. Academic Press, 1999.

[3] ——, "A theory for multiresolution signal decomposition: the wavelet representation," IEEE Trans. Patt. Recog. and Mach. Intell., vol. 11,no. 7, pp. 674–693, July 1989.

[4] E. P. Simoncelli, "Modeling the joint statistics of images in the wavelet domain," in Proc. SPIE 44-th Annual Meeting, 1999, pp. 188–195.

[5] K. Mihc¸ak, I. Kozintev, K. Ramchandran, and P. Moulin, "Low complexity image denoising based on statistical modeling of wavelet coefficients,"IEEE Signal Proc. Letters, pp. 300–303, Dec. 1999.

[6] S. G. Chang, B. Yu, and M. Vetterli, "Spatially adaptive image wavelet thresholding with context modeling for image denoising," IEEE Trans. Image Proc., vol. 9, no. 9, pp. 1522–1531, Sep. 2000.

[7] M. Crouse, R. D. Nowak, and R. G. Baraniuk, "Wavelet-based signal processing using hidden Markov models," IEEE Trans. Signal Proc. (Special Issue on Wavelets and Filterbanks), vol. 46, pp. 886–902, Apr. 1998.

[8] J. K. Romberg, H. Choi, and R. G. Baraniuk, "Bayesian tree-structured image modeling using wavelet-domain hidden Markov models," IEEE Trans. Image Proc., vol. 10, no. 7, pp. 1056 –1068, Jul. 2001.

[9] M. J. Wainwright, E. P. Simoncelli, and A. S. Willsky, "Random cascades on wavelet trees and their use in modeling and analyzing natural images," Journal of Appl. and Comput. Harmonic Analysis, vol. 11, pp. 89–123, Jul. 2001.

[10] J. M. Shapiro, "Embedded image coding using zerotrees of wavelet coefficients," IEEE Transactions on Signal Processing, Special Issue on Wavelets and Signal Processing, vol. 41, no. 12, pp. 3445–3462, December 1993.

[11] S. M. LoPresto, K. Ramchandran, and M. T. Orchard, "Image coding based on mixture modeling of wavelet coefficients and a fast estimation quantization framework," in Proc. IEEE Data Compression Conf., 1997, pp. 221–230.