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A New Approach for Recognition of Facial Expresion Rate (Fer) Based On Tensor Perceptual Color Framework

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ABSTRACT
This paper proposes facial expression recognition in perceptual color space. Tensor perceptual color framework is introduced in this paper for facial expression recognition (FER), which is based on information contained in color facial images. TPCF enables multi linear image analysis in different color space, and demonstrate the color components give the additional information for the robust FER. Using this framework, the components (in either RGB, CIELab or CIELuv, YCbCr space) of color images are unfolded to 2-D tensors based on multi linear algebra and tensors concepts, from which the feature are extracted by Log-Gabor filters. The mutual information quotients method is employed for the feature selection. Features are classified using multiclass linear discriminate analysis classifiers.

I. INTRODUCTION

Color feature mat provides more robust classification results. Research reveals that the color information enhance the face recognition and image retrieval performance [8]-[11]. In [8] it was first reported in that taking color information enhance the reorganization rate as compared with the same scheme using only the luminance information. Liu and Liu in [10] proposed a new color space for face recognition. In [11] Young, Man and Plataniotis demonstrated that the facial color cues express the improved face recognition performance using the low-resolution face image. The RGB color tensor has enhanced the FER performance but it does not consider the different illumination was reported in [7]. Recent research shows the improved performance by embedding the color components. The capability of the color information in the RGB color space in terms of the recognition performance depends upon the type and angle of the light source, often making recognition impossible. Thus the RGB may not be always be the most desirable space for processing color information. In this issue can be addresses using perceptually uniform color system. In this paper a novel tensor perceptual color framework (TPCF) for FER is introduced which provides the information about the color facial images and investigates performance contained in the color facial images and investigates performance in perceptual color space under slight variation in the illumination.

II. construction of an image-based FER

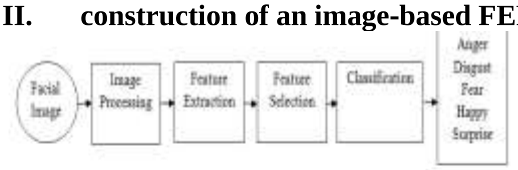
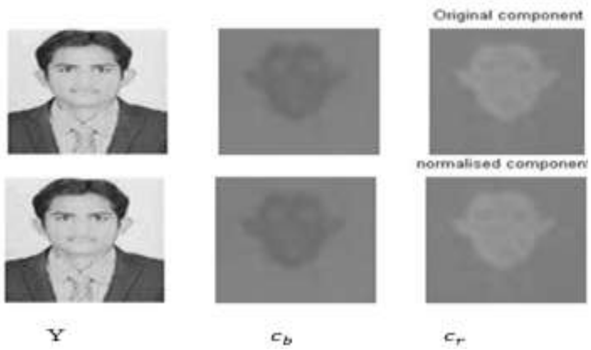


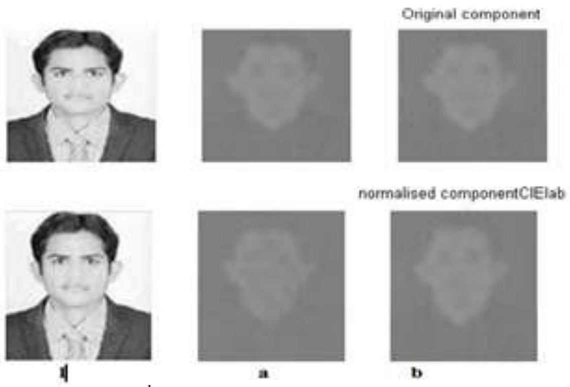
Figure. System level Diagram

The system level diagram of FER system shown in Figure The following section will describe briefly about YCbCr, CIELab, and RGB [13]

A. Face Detection and Normalization.



Color normalization is used to reduce the lighting effect because the normalization process is actually a brightness elimination process. Input image of $N_1 \times N_2$ pixels represented in the RGB color space,



$X = \{X^{n_3}[n_1, n_2] \mid 1 \le n_1 \le N_1, 1 \le n_2 \le N_2, 1 \le n_3 \le 3\}$

the normalized values, $X^{n_s}_{norm}[n_1, n_2]$, are defined by

$$X^{n_s}_{norm}[n_1, n_2] = \frac{X^{n_s}[n_1, n_2]}{\sum_{n_s=1}^{3} X^{n_s}[n_1, n_2]} \quad (1)$$

Where $X^{n_s}_{norm}[n_1, n_2]$ for $n_3 = 1,2,3$ corresponding to red, green, and blue (or R, G, and B) components of the image X.

It is obvious that

$$\sum_{n_s=1}^{3} X^{n_s}_{norm}[n_1, n_2] = 1 \quad (2)$$

Figure.2. Facial expression images: (a) YCbCr(b) lab space

B. Feature Extraction

The Log-Gabor filter, is Gaussian when viewed on a logarithmic frequency scale instead of a linear. It allows more information to be capture in the high-frequency area with desirable high pass characteristics. A bank of 24 Log-Gabor filter is employed to extract the facial features. Polar form of 2-D Log-Gabor filters in frequency domain is given by

$$H(f,\theta) = exp\left\{\frac{-\left[\ln\left(\frac{f}{f_0}\right)\right]^2}{2\left[\ln\left(\frac{\sigma_f}{f_o}\right)\right]^2}\right\} exp\left\{\frac{-(\theta-\theta_0)^2}{2\sigma_\theta^2}\right\} \quad (3)$$

where $H(f,\theta)$ is frequency response function of the 2-D Log-Gabor filter, f and θ denotes the frequency 2-D Log-Gabor filters, f and θ denotes the frequency and the phase/angle of the filter. f_o is the filter center frequency and θ_0 the filter's direction. The constant σ_f defines the radial bandwidth B in octaves and the constant σ_θ angular bandwidth $\Delta\Omega$ in radians.

$$B = \sqrt[2]{\frac{2}{ln2}} \times \left|ln\left(\frac{\sigma_f}{f_0}\right)\right|, \Delta\Omega = 2\sigma_\theta\sqrt{\frac{2}{ln2}} \quad (4)$$

In this paper describes here, the ratio σ_f / f_0 is kept constant for varying f_0, B is set to one octave and the angular bandwidth is set to one octave and the angular bandwidth is set to $\Delta\Omega = \pi/4$ radians. σ_f is be determined for a varying value of f_0. Six scales and four orientations are implemented to extract features from face images. It leads to 24 filter transfer functions representing different scales and orientations.

C. Feature Selection

Feature selection module have a distinctive features of image and it help us to improve the performance of the learning models by removing the most relevant and redundant features from the feature space. Optimum features are selected using minimum redundancy maximum relevance algorithm based on mutual information (IM). In presents a mutual information quotient (MIQ) method for feature selection and adopted to select the optimum features. As per the MIQ features selection if a feature vector has expression randomly or uniformly distributed in different classes and its MI with these classes is zero. If a feature vector is different from the other features for different classes, it will have large MI. Let F denotes the feature space; C denotes a set of classes $C = \{c_1, c_2, \ldots, c_k\}$, and v_t denotes the vector of N observation for that feature

$$v_t = [v_t^1, v_t^2, \ldots, v_t^N]^T \quad (5)$$

where v_t is an instance of the discrete random variable V_t. The MI between features V_t and V_s is given by

$$I(V_t; V_s) = \sum_{v_t \in V} \sum_{v_s \in V_s} p(v_t, v_s) log \frac{p(v_t, v_s)}{p(v_t)p(v_s)} \quad (6)$$

where $p(v_t, v_s)$ is the joint probability distribution function (PDF) of V_t and V_s, $p(v_t)$ and $p(v_s)$ are the marginal PDFs of V_t and V_s, for $1 \le t \le N_f$

,$1 \leq s \leq N_f$, and N_f is the input dimensionality, which equals the number of features in the dataset. The Mi between the V_t and C can be represent by entropies [19]

$$I(v_t; C) = H(C) - H(C|v_t) \quad (7)$$

where

$$H(C) = -\sum_{i=1}^{k} p(C_i)\log(p(C_i)) \quad (8)$$

$$H(C|V_t) = -\sum_{i=1}^{k}\sum_{v_t \in V_t} p(C_i, v_t)\log(p(C_i|v_t)) \quad (9)$$

where H(C) is the entropy of C, $H(C|V_t)$ is the conditional entropy of C on V_t, and k is the numbers of classes (for six expression, $k = 6$). The features (V_d) for desired feature subset, S, of the form $(S; c)$ where $S \subset F$ and $c \in C$ is selected based on solution of following problems:

$$V_d = arg\max_{V_t}\left\{\frac{I(V_t;C)}{\frac{1}{|S|}\sum I(V_t;V_s)}\right\} V_t \in \bar{S}, V_s \in S \quad (10)$$

where $\bar{S}$ is the complement features subset of S, $|S|$ is the number of features in subset S and $I(V_t; V_s)$ is the MI between the candidate features (V_t) and the selected feature and intra-class features is maximized. MI between the selected feature and inter-class features is minimized. These features are used for emotion classification.

D. Classification

The LDA classifier was studied for the same database and provides the better result than other classifiers [5]. The selected features using the aforementioned MIQ techniques are classified by a multiclass LDA classifier. In proposes a natural extension of Fisher linear discriminate that deals with more than two classes which uses multiple discriminate analysis. Projection from the high dimensional space to a low-dimensional space and the transformation descried to maximize the ratio of inter-class scatter (S_b) to the intra-class (S_w) scatter. The S_b can be viewed as the sum of square of distance between each class mean and the mean of all training samples. S_w can be regarded as the average class-specific covariance. Intra-class (S_w) and inter-class (S_b) matrices for feature vectors (X^f) are given by

$$S_b = \sum_{i=1}^{N_c} m_i(X^f_{\mu_i} - X^f_{\mu})(X^f_{\mu_i} - X^f_{\mu})^2 \quad (11)$$

$$S_w = \sum_{i=1}^{N_c}\sum_{X^f \in c_i}(X^f - X^f_{\mu_i})(X^f - X^f_{\mu_i})^T \quad (12)$$

where N_c is the number of classes (i.e., for six expression, $N_c = 6$), m_i is the number of training samples for each class. c_t is the class label, $X^f_{\mu_i}$ is the mean vector for each class samples (m_i), and X^f_{μ} is the total mean vector over all training sample (m) defined by

$$X^f_{\mu_i} = \frac{1}{m_i}\sum_{X^f \in c_i} X^f \quad (13)$$

$$X^f_{\mu} = \frac{1}{m}\sum_{i=1}^{N_c} m_i X^f_{\mu_i} \quad (14)$$

After obtaining S_w and S_b based on Fisher's criterion the linear transformation, W_{LDA}, can calculated by solving the generalized Eigen value (λ) problem

$$W^T_{LDA} S_b = \lambda W^T_{LDA} S_w \quad (15)$$

The transformation W_{LDA} is given the classification can be performed in the transformed space based on preformed distance measure such as the Euclidean distance, $\|\bullet\|$. The instance, X^f_n, is classified to

$$C_n = arg\min_i \|W_{LDA}X^f_n - W_{LDA}X^f_{\mu_i}\| \quad (16)$$

where c_n denotes the predicted class-label for X^f_n and X^f_n is the centriod of the ith class.

(20)

$$a = 500 \times \left(f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right) \quad (21)$$

$$b = 200 \times \left(f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right) \quad (22)$$

where X_n, Y_n, and Z_n are the reference white tristimulus value which are defined in CIE chromaticity diagram [21] and

$$f(t) = \begin{cases} t^{\frac{1}{3}}, & t > 0.008856 \\ 7.787 \times t + \frac{16}{116}, & t \leq 0.008856 \end{cases} \quad (23)$$

for u and v color components, the conversion is defined by

$$u = 13 \times L \times (u' - u'_n) \;\; v = 13 \times L \times (v' - v'_n) \quad (24)$$

The equation for $v^{'}$ and $u^{'}$ are given below

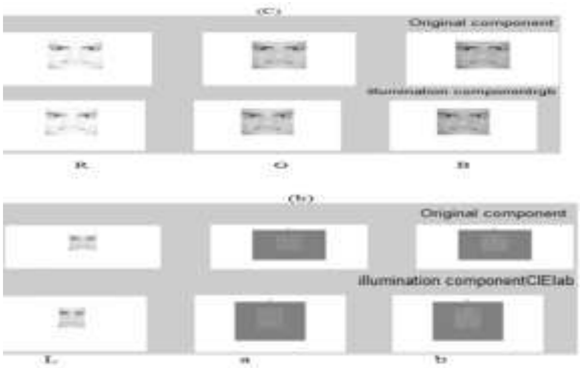
$$u^{'} = \frac{4X}{X+15Y+3Z} \quad (25)$$

$$v^{'} = \frac{9Y}{X+15Y+3Z} \quad (26)$$

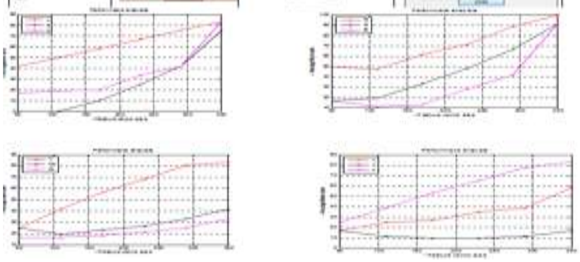
The quantities u'_n and v'_n are the $(u^{'}, v')$ chromaticity coordinates of a specific white object defined by

$$u'_n = \frac{4X_n}{X_n+15Y+3Z} \quad v'_n = \frac{9Y}{X_n+15Y_n+3Z} \quad (27)$$

III. Facial Expression Images under Illumination:



IV. Experimental Results



V. CONCLUSION

Tensor based feature level facial expression approach is proposed in this paper, the present is evaluated with the Indian face data base under different color transformations and resolution and it is shown that the CIE-Lab and CIE-LUV transformation outperforms the highest recognition rate

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