Journal of Engineering and Development, Vol. 16, No.4, Dec. 2012 ISSN 1813- 7822

Face Recognition under Illumination Changes Using Color Fast and Adaptive Bi-Directional Empirical Mode Decomposition

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Abstract

Recently, the importance of face recognition in color images has been increasingly emphasized since popular CCD cameras are distributed to various applications. However, face feature extracted from the image will distorted non-linearly by lighting variations in intensity or directions, so this changes will cause a serious performance degradation in face recognition. Many algorithms adopted by researchers to overcome the illumination problem. Most of them need multiple registered images per person or the prior knowledge of lighting conditions. According to the "common assumption" that illumination varies slowly and the face intrinsic feature (including 3D surface and reflectance) varies rapidly in local area, high frequency feature represents the face intrinsic structure. The Fast and Adaptive Bi-dimensional Empirical Mode Decomposition FABEMD has been extended for color image analysis. The proposed algorithm, based on the powerful transform for the color image named color FABEMD (CFABEMD). The color image decomposed into multi-layer high frequency images representing detail feature and low frequency images representing analogy feature. In addition a two measurements are proposed to quantify the detail feature that use to eliminate illumination variation, with these measurement weights, CFABEMD based multi-layer detail images recognition can be done under vary illumination. With PCA, the experiment results based on processed CVL database and Georgia Tech Face database show the method can get remarkable performance.

Key words **:** illumination invariant, BEMD, CFABEMD, face recognition

تمييز الوجوه تحت انارة مختلفة باستخدام تحليل النمط التجريبي ثنائي الابعاد والمتكيف السريع المطور للصور الملونة

الخلاصة

ان الميزات المستخرجة من الصور والمعتمدة للتمييز بين الصور او الوجوه تتشوهة بصورة غير خطية من قبل الاختلافات في شدة الإضاءة أو أتجاهاتها، ولهذا فان هذه التغييرات سوف تؤدي إلى تدهور في أداء انظمة التعرف على الوجوه. العديد من الخوارزميات التي اعتمدت من قبل الباحثين للتغلب على مشكلة الإضاءة بحاجة لعدة صور للشخص الواحد أو على علم مسبق لظروف الإضاءة. بالاعتماد على الفرضية المعروفة التي تنص بأن التغير في الانارة يكون طفيفاً لمنطقة محددة وان الميزات الجوهرية في الوجة يكون تغيرها كبير فان الميزات عالية التردد المستخرجة من الوجة في تلك المنطقة ستمثل الميزات الجوهرية. وقد تم استخدام تحليل النمط التجريبي ثنائي الابعاد والمتكيف السريع المطور والقادر على تحليل الصور الملونة حيث يتم تحليل الصورة الى عدة مستويات وبالإضافة لذلك تم اقتراح كميتين لقياس ميزات التفاصيل وباستخدام تلك القيمتين امكن تجاوز تباين الإضاءة في التمييز بين الوجوه. اجريت التجارب على قاعدتين للبيانات (صور) وهما قاعدة مختبر الابصار الكومبيوتري لجامعة لجويلجانا CVL اما القاعدة الاخرى فهي قاعدة صور معهد جورجيا التقني Georgia Tech وكانت النتائج عالية في الأداء. بعد مقارنتها بالطرق الاخرى.

Introduction

In the case of controlled environmental, face recognition systems can achieve very satisfactory results. But some environmental situation is not controllable, face many challenges, such as illumination changes, facial gestures, facial expressions, and so on. Especially in natural lighting conditions, face recognition due to light intensity, direction, and the non-linear interference becomes very difficult[1]. It is believed that variations caused by lighting in face images are even larger than differences among distinct individuals[2, 3].

In order to eliminate the impact of illumination changes on face recognition, the researchers made a lot of work in the past decade; there have been many effective methods[4]. Among them, active three-dimensional face[5], active near-infrared face[6]and thermal infrared face[7] because it is not within the visible spectrum of face images, which can be very good solution to light interference. But they require additional collection devices, and those who need to test with the use of close, so the actual use of face recognition systems is limited. Therefore, most studies focused on the use of the visible spectrum, or within the face image area.

PCA (Eigenface)[8]and LDA (Fisherface)[9]are applied to the training set which contains faces under different illuminations to achieve a subspace which covers the variation of possible illumination[4]. However, if there are dramatic differences in light for the training set or test set, then the effect of such an approach will be greatly reduced. Georghiades[10]and Basri[11]proposed a 2D face mapped to 3D face modeling method to eliminate the illumination effect, although experimental data show that this method can be very superior recognition results, but its computational complexity problems have hindered its for the actual system. LBP (Local Binary Pattern)[12]is a very simple and effective method of texture analysis and face recognition, it only takes into account the size of the relationship between pixel values in the local area, and give up easily affected by the contrast of light relationship, so It can eliminate the non-linear illumination changes caused by interference. However, as compared with other methods, LBP face recognition is not very good. Bhuiyan[13]use the neural network and Gabor filter in the face recognition. Zhang[14]using wavelet de-noising technique to eliminate the noise that made by a kind of illumination, but this method need experience to specify a domain's threshold parameter, thus its universal application is affected. Shao[15]and Chen[16]proposed an effective face illumination normalization method by using the fast and adaptive bi-dimensional empirical mode decomposing FABEMD. Experiments prove that methods can greatly enhance the face recognition rates. But they still used to gray level only.

During past years, most researches have been conducting on gray images. But recently, thanks to high quality digital cameras, researchers can take precise color images and do suitable study on them by fewer amounts of costs. Early color images had low quality, and that is why work on them was started later than work on gray images. Most of the recognition technique under varying illuminations use an illumination normalization prior to the recognition process, some of these normalizations are multiscale retinex algorithm (MSR)[17], self-quotient image (SQI)[18]and isotropic smoothing methods[19].

In this paper, FABEMD based face recognition has been extended for color image analysis. The proposed algorithm, based on the powerful transform for the color image named color FABEMD (CFABEMD)[20], is known to be the first approach of color face recognition based on BEMD.

Finally, We compared the proposed with principal component analysis (PCA)[8], linear discriminate analysis (LDA)[9], and Gabor[13]methods, after applying the above normalization technique to overcome the illuminations effects, to see the performance of the proposed system. Experiments result show that superior recognition rates under varying illumination.

Decomposition Overview

Face Image Representation

According to intrinsic image decomposition model face image can be described as[21]:

$$I(x,y) = R(x,y) * \quad . . . . (1)$$

Where, I (x, y) represents the value of the face image's pixel, R (x, y) represents the face skin reflectivity to the light, and L (x, y) represents the illumination image. It can be assumed in the local area of face that the light L (x, y) changes more slowly hence reflect the essential features of the face rather than rapid changes in reflectivity. Slowly changing signal is low-frequency signal and rapidly changing signal is high-frequency signal. As to the illumination invariant face recognition, obtaining small-scale features, for example the edges or corners of nose, eyes or mouth, is critical and this feature generally falls in high-frequency area of the image. Meanwhile, the large-scale feature contains the illumination information such as specularity or shadows as well as larger intrinsic component, lies in low-frequency area. In this article, it can be said images that have a large number of high frequency signals mean it have a lot of details.

Color Face Image Decomposition with CFABEMD

EMD (Empirical Mode Decomposition) an adaptive decomposition which was proposed by Huang and et al[22,23,24], is appropriate for non linear, non-stationary one dimensional signal decomposition. The concept of EMD is to decompose the signal into a set of zero mean functions called Intrinsic Mode Functions (IMF) and a residue, each IMF containing different scales of frequency signals. This signal decomposition technique is extended to two-dimensional signal, known as two-dimensional empirical mode decomposition (Bi-dimensional Empirical Mode Decomposition, BEMD) [25,26,27].Similarly, BEMD can be decomposed image into Bi-dimensional IMF (BIMF), each BIMF containing a different scale of two-dimensional frequency signal. BIMF1 is the first to get BEMD decomposition, it contains the most high-frequency signals, while the rest of the BIMF which have more low-frequency signals.

BEMD is time-consuming method since it requires surface interpolation, this making it dramatically increases the time and complexity, which makes it difficult to be applied to practical applications. To address this shortcoming, Bhuiyan[28,29,30] proposed a fast adaptive FABEMD method. It substitutes the 2D scattered data interpolation step of BEMD by a direct envelope estimation method. In this technique a spatial domain sliding order-statistics filters (OSF) namely MAX and MIN filters are utilized to obtain the running maxima and minima of the data, respectively. Application of smoothing operation to the running maxima and minima results in the desired upper and lower envelopes respectively. It has been shown that the FABEMD not only provides faster decomposition, but also provides BIMFs with relatively less distortion or other artifacts. It can also be applied to images of any resolution/size without any difficulty or time constraints[20].

On the contrary of the BEMD, it is appear that FABEMD is a good choice for the Color BEMD (CBEMD) due its properties. The details of the FABEMD can be found in[28,29].

CBEMD Process

Let a color image be denoted as $I^p(x, y)$, where, p is the color index of the color image component CIC (*i.e.*, $p=1, 2, and\ 3$), and (x, y) is the pixel coordinate for $m \times n$ local area of the color image. Similarly, denote i-th BIMF of the CIC (CBIMFC) as $F_i^p(x, y)$ and the residue (CBRC) is represented as $R^p(x, y)$. F_i^p in the decomposition process is obtained from it source

S_i^p, where S_i^p is the residue image obtained as $S_i^p = S_{i-1}^p - F_i^p$ and $S_1^p = I^p$. The steps of the color FABEMD (CFABEMD) process can summarized[20] as follow:

i. Set $i = 1$, and $S_i^p = I^p$ for $p=1, 2, and\ 3$. If S_i^p (*i.e.* I^p) do not have the BR properties for all p's, then go to step (*ii*).

ii. Obtain the local maxima and minima maps of S_i^p, denoted as $P_i^{s\text{-}p}$ and $Q_i^{s\text{-}p}$, respectively, using neighboring window method (NWM).

iii. Calculate the size of the order-statistics filters (OSFs) and smoothing averaging filters (SAFs) from $P_i^{s\text{-}p}$ and $Q_i^{s\text{-}p}$. (This step is explained later).

iv. Generate the UEs U_i^p, and the LEs L_i^p, of source CICs S_i^p using the OSFs from step (*iii*). (This step is explained later).

v. Obtain the smoothed UEs $\bar{U}_i^p(x,y)$, and the smoothed LEs $\bar{L}_i^p(x,y)$, from $U_i^p(x,y)$, and $L_i^p(x,y)$, respectively, using the SAFs from step (*iii*). (This step is explained later).

vi. Find the smoothed mean envelopes (MEs) as $M_i^p = (\bar{U}_i^p + \bar{L}_i^p)/2$.

vii. Calculate F_i^p as $F_i^p = S_i^p - M_i^p(x,y)$ for all p's.

viii. Set $S_{i+1}^p = S_i^p - F_i^p$ for all p's, and $i = i + 1$; go to step (*ix*).

ix. Find out the number of extrema points (maxima and minima together) (NEP), denoted as ε_i^{2-p} in S_i^p for all p's. If ε_i^{2-p} is less than the extrema threshold (ET) ε^{2T} for any p, the CBRCs $R^p = S_i^p$; and the decomposition is complete. Otherwise, go to step (*ii*) and continue up to step (*ix*). The standard value for ET, $\varepsilon^{2T} = 2$. Stopping the decomposition when ET is achieved for any of the source CICs, ensures the same number of BIMFs for each CIC.

For simplicity the *i-th* CBIMF, $F_i^p(x, y)$, will be called CBIMF-*i*. And when talking about CBIMFs and the CBR of a color image together will named as CBEMFs, where the first CBIMF is the first CBEMF (CBEMF-1) and the CBR is the final CBEMF. Also the *i-th* CBEMF can be denoted as $C_i^p(x, y)$ having three CBEMF components (CBEMFCs) for three values of p. If no processing is done on the CBEMFCs, the summation of the CBEMFCs results in the original CICs[20,28].

Envelope Estimation in CBEMD

Envelop in CBEMD can be estimated by using neighboring window method (NWM) with 3×3 window[25,29]is employed to find the local maxima and minima maps P_i^{S-p} and Q_i^{S-p} from the source CICs. After obtaining the above maps two order statistics filters (OSFs) are employed to approximate the UEs and LEs, where a *MAX* filter is used for the UEs and a *MIN* filter is used for the LEs. For each local maximum (minimum) point in P_i^{S-p} (Q_i^{S-p}), the Euclidean distance to the nearest other local maximum (minimum) point (non-zero element) is calculated and stored in 1D arrays, denoted as λ_i^{U-p} (λ_i^{L-p}), where $p=1, 2\ and\ 3$; and i is the index of the CBIMFs or source CICs. The distances in all three arrays (for all three p's) of the maxima or minima distances obtained from all three source CICs are then combined to obtain one array for the maxima distances and one array for the minima distances in the following manner:

$$\lambda_i^U = [\lambda_i^{U\text{-}1} \quad \lambda_i^{U\text{-}2} \quad \lambda_i^{U\text{-}3}], \qquad (2)$$

$$\lambda_i^L = [\lambda_i^{L\text{-}1} \quad \lambda_i^{L\text{-}2} \quad \lambda_i^{L\text{-}3}], \qquad (3)$$

Considering square window, the gross window width for the OSFs corresponding to the source CICs $S_i^p(x, y)$ can be selected in different ways using the distance values in λ_i^U or λ_i^L, one of which is[28]

$$w_i^{en-g^{LD}} = \min\{\min\{\lambda_i^U\},\min\{\lambda_i^L\}\} \qquad (4)$$

Where $min\{.\}$ denotes the minimum value of the elements in the array $\{.\}$. The order statics filters (OSFWs) obtain from all type of gross OSFW's is generally denote as w_i^{en-g} and when use the lowest distance OSFW (LDOSFW) as in equ.4, it will denote as $w_i^{en-g^{LD}}$. They are rounded to the nearest higher odd integer to get final window width w_i^{en} for extracting i-th CBENF. The use of LD-OSFW for the decomposition results in more number of BIMFs compared to the use of other types of OSFW.

The w_{i+1}^{en} appears larger than w_i^{en} in most of the cases, sometimes w_{i+1}^{en} may become smaller than or equal to w_i^{en} if using LD-OSFW. Therefore, additional manipulation can be done to make it larger (*e.g.* w_{i+1}^{en} may be taken as approximately as, $w_{i+1}^{en} = 1.5 \times w_i^{en}$). With the determination of OSFW w_i^{en} for envelope estimation, *MAX* and *MIN* filters can applied to the corresponding source CICs $S_i^p(x, y)$, to obtain the UEs $U_i^p(x, y)$ and the LEs $L_i^p(x, y)$, as specified below:

$$U_i^p(x, y) = MAX_{(s,t)\in Zxy}\{S_i^p(s, t)\} \qquad (5)$$

$$L_i^p(x, y) = MIN_{(s,t)\in Zxy}\{S_i^p(s, t)\} \qquad (6)$$

In Eq. 5 (Eq.6), the values of the UEs $U_i^p(x, y)$ (LEs $L_i^p(x, y)$) at any point (x, y) are simply the maximum (minimum) values of the elements in $\{.\}$ in the region defined by Z_{xy}, where Z_{xy} is the square region of size $w_i^{en} \times w_i^{en}$ centered at any point (x, y) of $\{.\}$. So, the UEs (LEs) are obtained by running the *MAX (MIN)* filter over all the pixels of the source CICs $S_i^p(x, y)$, and taking the maximum (minimum) values of the elements of $S_i^p(x, y)$ encompassed by the *MAX (MIN)* filter for the original pixel corresponding to the center of the *MAX (MIN)* filter. It can be noted that the same size for the OSFs (*i.e.*, *MAX* and *MIN* filters) is used for extracting all three CBIMFCs for a particular CBIMF. Hence, similar and correlated local spatial scales are extracted into all three CBIMFCs for the corresponding CBIMF.

To obtain nearly smooth continuous surfaces for the UEs and LEs, smoothing averaging operations are carried out on both, which may be expressed

$$\bar{U}_i^p(x,y) = \frac{1}{w_i^{sm}\times w_i^{sm}} \sum_{(s,t)\in Z_{xy}} U_i^p(s,t) \qquad (7)$$

$$\bar{L}_i^p(x,y) = \frac{1}{w_i^{sm}\times w_i^{sm}} \sum_{(s,t)\in Z_{xy}} L_i^p(s,t) \qquad (8)$$

Where Z_{xy} is the square region of size $w_i^{sm}\times w_i^{sm}$ centered at any point (x, y) of $\{.\}$. w_i^{sm} is size of the SAF and it is generally taken $w_i^{sm} = w_i^{en}$ for a particular CBIMF. To achieve the same goal of extracting similar and correlated local spatial scales among the CBIMFCs for a particular CBIMF, same sized SAFs are applied for three color components of the envelopes obtained by the OSFs.

CFABEMD method decomposed color face image into $CBIMF_1$, $CBIMF_2$ ..., $CBIMF_k$ $(k = 1, 2, ..., N)$, each representing a different frequency scale CBIMF details of the image. In figure 1 given an example of decomposing a human face images of the three-scale details.

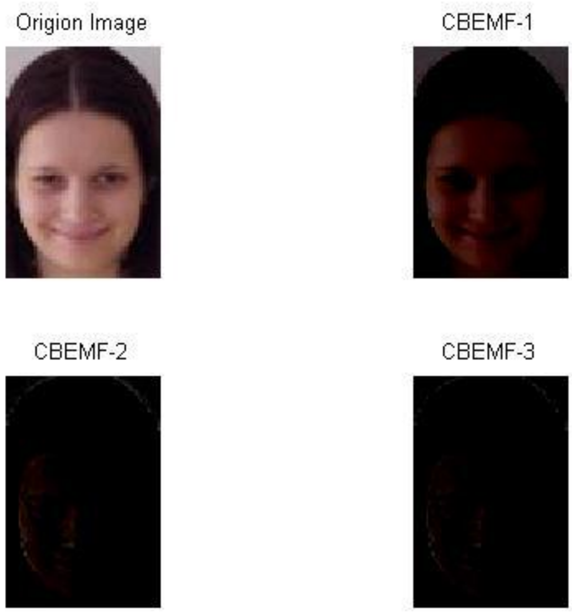

Fig. 1. (Left to right, and top to bottom) color image from CVL, and its CBEMF-1 to CBEMF-3 obtained with LD-OSFW.

Proposed Algorithm

Features Integration of Multi-Scale image Details

A framework calculation proposed to integrate the multi-scale details characteristic, the extracted features of each image in multi-scale image detail decomposition of the images taken together. Enhance the face recognition accuracy result through regulation the integration weight coefficients of the details characteristic. Computational framework is as follows:

$$D = \lambda_1 d_1 + \lambda_2 d_2 + \ldots\ldots + \lambda_n d_n = \sum_{i=1}^{n} \lambda^{p}_{i}\, d_i \qquad (9)$$

Where D is the characteristic distance between two images, d_i is the characteristic distance between the $i'th$ layer of the detail images, λ_i is the distance weight coefficient, which reflects the contribution of the i-layer image feature details distance to the whole value of the distance D. Although high-frequency details of the images contain more detail and texture features, but contains less facial structure and contour information. From a cognitive perspective, structure and contour information more useful to target identification, so the contribution of the distance between the low-frequency image feature details to the global distance greater than the contribution of the high-frequency image feature details. So that $\lambda_1 < \lambda_2 < \ldots < \lambda_n$, and $\sum_{i=1}^{n} \lambda^{p}_{i} = 1$.

Suppose there are two images I and I' need to measure the characteristics distance, after the image decomposition operation, get n-levels image details for each component I^{p}_{1}, I^{p}_{2}, ... , I^{p}_{n} and I'^{p}_{1}, I'^{p}_{2}, ... , I'^{p}_{n}, respectively, d_i is the characteristic distance between the features I_i and I_i'. If find a certain method of details information measurement M, the measurement information value for every image details is MI^{p}_{1} , MI^{p}_{2} , ... , MI^{p}_{n} and MI'^{p}_{1} , MI'^{p}_{2} , ... , MI'^{p}_{n}, so you can use the following formula to calculate the value of λ_i:

$$\lambda_i = \sum_{i=1}^{n} \lambda^{p}_{i} = \frac{\frac{1}{MI^{p}_{n}} + \frac{1}{MI'^{p}_{n}}}{\sum_{i=1}^{n} \frac{1}{MI^{p}_{i}} + \sum_{i=1}^{n} \frac{1}{MI'^{p}_{i}}} \qquad (10)$$

It can be seen that λ_i is the proportion calculated from the information amount in $i'th$ layer detail of images I and I' with reciprocal to the information amount in all the images details, so it can be effective and used in all light conditions and cases.

Information measurement methods of the image feature details

Two measurement methods proposed to calculate the information amount of image feature details.

The number of extreme point measurement method

Image feature details contains a large number of contour curves describe the objects. The more abundant of these edge curves, the more essential characteristics of the object and then the more detailed description. The edge curves in the local area of images are the distribution of number of consecutive maximum or minimum pixel component values. The total number of extreme points (EP_k), which is the sum of three components EP^1_k, EP^2_k and EP^3_k, can be used as a measure of how much the details images contain information. The formula as follow:

$$EP_k^p = \sum_{x}^{w}\sum_{y}^{h} (|\{P_c|P_c>P_i\}|+|\{P_c|P_c<P_i\}|) \qquad (P_i \in A_c) \tag{11}$$

$$EP_k = \sum_{k=1}^{3} EP_k^p \tag{12}$$

Where w, h are the width and height of the image details I_k , P_C is the pixel with coordinates (x, y), A_C is $N\times N$ local area that P_C pixel is its center, P_i is the points within A_C with P_C removed and any other pixels outside A_C, $i = 1,2, .. n\times n\text{-}1$. Figure 2 shows the EP_k values with image details layers k value change 1- 6 based on 100 images. We can show that the number of extreme point in the first CBEMF is greater than those in the second CBEMF and so on.

Contrast measurement method

Contrast refers to the difference between value of image pixels for each color image component, it is clear that the greater difference pixels are easily distinguished by the human eye, then the greater amount of information expressed in the image. The low order CBEMD (CBEMD-1) obtained after the multi-level decomposition of the image, will contains more amount of information, then its value must be relatively large, in contrary, high order CBEMD that contains less information amount, it must be relatively small. Therefore, the contrast value CV_k (sum of three local contrast component CV_k^p) can be used as a measure of how much the image details contain information. The formula as follow:

$$CV_k^p = \sum_{x=1}^{w}\sum_{y=1}^{h}\sqrt{\sum (P^p{}_c - P^p{}_i)^2} \qquad (P_i \in A_c) \tag{13}$$

$$CV_k = \sum_{k=1}^{3} CV_k^p \tag{14}$$

Where w, h are the width and height of the image details I_k, P_C is the pixel with coordinates (x, y), A_C is $N{\times}N$ local area that P_C pixel is its center, P_i is the points within A_C with P_C removed and any other pixels outside A_C, $i = 1,2, .. n{\times}n\text{-}1$. Figure 3 shows the CV_k values with image details layers k value change 1-6 based on 100 images.

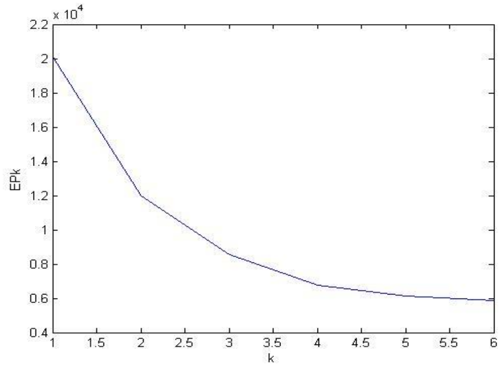

Figure 2: shows EP_k with image details layers k value change 1-6 based on 100 images.

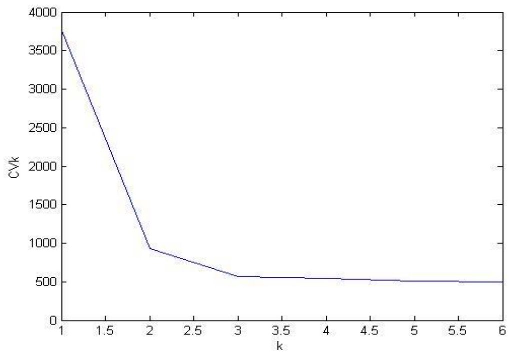

Figure 3: The CV_k values with image details layers k value change 1-6 based on 100 images

Calculating the framework's weights of the measurement methods:

Since the value of the measurements above (Fig.2 and 3) monotonically decrease with the decomposition series that decreasing, these values are characterized by its own image through the calculated image details, and because there is no external argument required hence these values CV_K and EP_K are at least relative to amount of information. So, you can apply EP_K and CV_K to the computing fusion framework. Using EP_K and CV_K obtain the measured values EP_i and EP_i', CV_i and CV_i' for images I and I' respectively at image details level i, substituting them in the equation (10), obtained the following two kinds of weighting coefficient calculation framework program λ_{EP} and λ_{CV}:

$$\lambda^p{}_{EP\,i} = \frac{\frac{1}{EP^p_i} + \frac{1}{EP'^p_i}}{\sum_{j=1}^{n} \frac{1}{EP^p_j} + \sum_{j=1}^{n} \frac{1}{EP'^p_j}} \quad (15)$$

$$\lambda^p{}_{CV\,i} = \frac{\frac{1}{CV^p_i} + \frac{1}{CV'^p_i}}{\sum_{j=1}^{n} \frac{1}{CV^p_j} + \sum_{j=1}^{n} \frac{1}{CV'^p_j}} \quad (16)$$

$$\lambda_{EP} = \sum_{p=1}^{3} \lambda^p{}_{EP_i} \quad (17)$$

$$\lambda_{CV} = \sum_{p=1}^{3} \lambda^p{}_{CV_i} \quad (18)$$

Experiments and Results

In order to test the efficiency of the algorithm presented above, a series of experiments performed using two different sets of test images. The first set is extracted from the CVL[31] and the second is Georgia Tech face[32] color face database.

CVL database contains color face images of 114 persons. Each person has 7 images with the resolution of 640x480 pixels. In this work, one front image of each person are selected after hand cut to remove the non-face area and resized to 100x150 pixels then applied to Ronen Basri[33] algorithm to represent the image in different illuminations, here the illumination's direction angles θ and φ changed as $(0^\circ,45^\circ,90^\circ,135^\circ,180^\circ)$ from left to right and from top to down respectively hence each person will have 25 image with different illumination condition and the total image will be 2850 image. 114 images taken as training set (i.e. one image for each person) and the other 2736 images as test set.

Georgia Tech Face database contains images of 50 people. All people in the database are represented by 15 color JPEG images with cluttered background taken at resolution 640x480 pixels hence will have 750 images as total. The average size of the faces in these images is 150x150 pixels. The pictures show frontal and/or tilted faces with different facial expressions, lighting conditions and scale. In this experiment the face images with the background removed are resized to 100x150 pixels. Three image for each person used to training and the rest 600 images used as test sets. Sample images from the two sets are displayed in figures 4 and 5.

Figure 4: Sample image from Georgia Tech face Database for same person

Figure 5: Sample image from CVL Database for same person after

Results

All experiments were performed using three level details for the processing, using the cosine distance as the feature vector distance measure, and use PCA as the minimum distance classifier. In both databases the proposed algorithm applied and compared with principal component analysis (PCA), linear discriminate analysis (LDA), and Gabor's method to see the performance of the proposed system. The recognition performed after applying the images to three illumination normalization techniques multiscale retinex algorithm (MSR)[17], self-quotient image (SQI)[18]and isotropic smoothing methods[19]to eliminate invariant illumination effects. Experiments result show that superior recognition rates under varying illumination.

Table 1: Comparison of the proposed technique with other illumination techniques for the two databases

Database	*Color-FABEMD*	*PCA*			*LDA*			*Gabor*		
		MSR	*SQI*	*Isotropic*	*MSR*	*SQI*	*Isotropic*	*MSR*	*SQI*	*Isotropic*
CVL	*96.32 %*	*82.4*	*80.5*	*81.4*	*83.6*	*82.4*	*79.8*	*86.2*	*89.7*	*80.3*
Georgia Tech face	*93.29 %*	*81.1*	*79.8*	*80*	*81.8*	*80.3*	*79.1*	*85.3*	*86.4*	*80.1*

Conclusion

Color FABEMD methods can simply and effectively decompose the image into several image details; each image detail contains number of different scales and different frequency characteristics of the details. High-frequency signals (low level image details) represents the facial characteristic details that is less affected by changes in light, and consider as illumination invariant features. This paper consider the characteristics of these scattered details and proposed a kind of fusion calculation method for color image, then proposed two methods to measure the information amount of image feature details thus it is estimated the fusion weight factor but does not required any arguments, so that it has adaptive characteristics.

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