Illumination Compensation of Facial Image
Using Combination Algorithm for Face Recognition

Duong Trong Luong*, Hoang Truong Kien, Nguyen Thanh Cong, Nguyen Thai Ha

Hanoi University of Science and Technology, No. 1, Dai Co Viet, Hai Ba Trung, Hanoi, Viet Nam

Abstract

So far, biometric identification in general and facial recognition in particular are still being researched and developed for applying in several areas such as security, etc. In this paper, the authors study on some facial image recognition methods that have been researched and published in the world. On the basis of the remaining disadvantages of these published methods, we proposed an illumination compensation method of facial image using Combination Algorithm for face recognition. It is combination method of Singular Value Decomposition and Curvelet algorithm (SVD_C). The results of this proposed method are compared with the results of Global Adaptive Singular Value Decomposition in the Fourier domain method (GASVD_F) and Adaptive Singular Value Decomposition in the Wavelet domain method (ASVD_W) via recognition rate criterion RR (%). Experimental results validate the efficiency of the proposed method.

Keywords: 2D discrete wavelet transform, face recognition, illumination compensation, singular value decomposition

1. Introduction

In the recent many years, face recognition has been one of most popular research topics in the area of computer vision, pattern recognition, and machine learning. Face recognition has been widely used in the real world, for example, for video surveillance, criminal investigation, access control, and content annotation in a Web environment. The performance of a face recognition system is considerably affected by the pose, expression, and illumination variations in face images [6]. Image treatment for illumination variation has been considered as one of the most critical preprocessing steps in face recognition [7]. Differences in illumination conditions can make the appearance of a face in an image change greatly. Lighting changes cause larger differences in facial images compared with pose variations [8]. In the real world, nonuniform light such as polarized light, side light, and high light cause over-bright, over-dark, or shadow regions in face images. Several published researches have introduced methods to solve the illumination problem. These methods can be separated into three major categories: illumination-invariant feature extraction, modeling face images as linear space, and illumination compensation or normalization. There are several researches on illumination compensation of image in face recognition systems such as an efficient illumination invariant face recognition framework via illumination enhancement and DD-DTCWT filtering [1]. Illumination invariant extraction for face recognition

using neighboring wavelet coefficients [2]; Variable lighting face recognition using discrete wavelet transform [3]. These methods have the defects that images in many cases are balanced but the histogram do not reach the required contrast level when the lighting source changes, or the lighting source has excessive intensity. To perform illumination normalization in face images captured under different lighting conditions, Marios Savvides and B.V.K. Vijaya Kumar introduced a method of logarithm transforms for face authentication [4]. Shan Du and Rabab Ward used Wavelet to perform illumination normalization for face recognition [5]. Chen *et al*. [9] used discrete cosine transform (DCT) to compensate for illumination variations in the logarithm domain. However, these methods are not the highest effective for images with a substantial change in the lighting conditions. Beside most of the methods attempt to resolve the illumination variation problem for grayscale face images, several methods have processed color face images recently. H. Demirel and G. Anbarjafari [10] employed singular value decomposition (SVD) for lighting compensation to reduce the effect of illumination on color images. In this method, only a Gaussian template is used for all three RGB color channels, resulting in loss of color information from the facial image. To overcome these shortcomings, J.W.Wang *et al*. [11] used the respective singular values of the three color channels (RGB) for illumination compensation; this method is called adaptive singular value decomposition (ASVD). Recently, several methods have been developed for image processing in the frequency domain, such as the Fourier domain and Wavelet

---
* Corresponding's author: Tel: (+84) 967008876
E-mail:luong.duongtrong@hust.edu.vn

domain [6],[12]. Wang *et al.* [6] performed reducing the influence of side light on a color face image when there is insufficient light and improving the capability of recognition systems. The method first transforms a color face image to the two-dimensional (2D) discrete Fourier domain and then adjusts the magnitudes of the three color channels automatically by multiplying singular value matrices of the three magnitude matrices of the RGB color channels with their compensation weight coefficients. This method is ASVD_F, it involves two steps. First, it computes the intensity distribution of the image to decide the type of illumination to which the image belongs: uniform lighting or lateral lighting. Then two variants of ASVDF with associated Gaussian templates are proposed: local ASVDF (LASVDF) for lateral lighting and global ASVDF (GASVD_F) for the uniform lighting. Second, to reduce the influence of light variation on face recognition, a novel method is applied to each individual magnitude matrix of the color channels of RGB. In addition, Wang *et al.* [12] proposed a method called adaptive singular value decomposition in the 2D discrete wavelet domain (ASVD_W) to overcome light variation in face recognition. Although these methods show high performance for the face matching task and are highly useful for face detection, but, we proposed another method to overcome light variation in face recognition and shows recognition rate might be better than these method's one. This paper presents combination method of Singular Value Decomposition and Curvelet algorithm to upgrade the contrast by brightness compensating for the RGB color channels of the face image therefore improve the face recognition rate. The results of this proposed method are compared with results of GASVD_F and ASVD_W methods and tested with CMU-PIE and FERET color image databases.

2. Methodology

2.1. Singular Value Decomposition

The proposed method uses combination algorithm of Singular Value Decomposition and Curvelet transform to upgrade the contrast by brightness compensating for the RGB color channels of the face image [12, 13]. With the SVD algorithm, any matrix **A** is separated into three matrices:

$$\mathbf{A} = \mathbf{USV^T} \qquad (1)$$

where: **U**, **V** are orthogonal matrices.

U contains vectors $\{u_1, u_2, u_3, \dots, u_r, u_{r+1}, \dots, u_m\}$ indicates vertical image properties.

V contains vectors $\{v_1, v_2, v_3, \dots, v_r, v_{r+1}, \dots, v_m\}$ indicates horizontal image properties.

And **S** is a diagonal matrix:

$$S = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_r & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \sigma_{r+1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & \cdots & \sigma_n \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \end{bmatrix}$$

The diagonal matrix **S** contains singular values σ_i where $i = 1, 2, \dots, n$

2.2. Transforming Curvelet

Curvelet is an extension of the wavelet transform, overcome inherent limitations of traditional multiscale representations such as wavelets. The curvelet transform is a multiscale pyramid with many directions and positions at each length scale, and needle-shaped elements at fine scales. Indeed, curvelet has useful geometric features that set them apart from wavelets [14]. Curvelet obeys a parabolic scaling relation which says that at scale 2^{-j}, each element has an envelope which is aligned along a "ridge" of length $2^{-j/2}$ and width 2^{-j}. An application of the phase-space localization of the curvelet transform allows a very precise description of those features of the object of f which can be reconstructed accurately from such data and how well, and of those features which cannot be recovered. Roughly speaking, the data acquisition geometry separates the curvelet expansion of the object into two pieces:

$$f = \sum_{n \in Good} \langle f, \varphi_n \rangle \varphi_n + \sum_{n \notin Good} \langle f, \varphi_n \rangle \varphi_n \qquad (2)$$

Continuous-Time Curvelet Transforms in two dimensions, with a spatial variant x, and ω is a frequency domain variant, and r and θ are polar coordinates in the frequency-domain [14]. A pair of windows *W(r)* and *V(t)* are called the "radial window" and "angular window" respectively. These are both smooth, nonnegative, and real-valued, with *W* taking positive real arguments and supported on $r \in (1/2, 2)$ and *V* taking real arguments and supported on $t \in [-1, 1]$. These windows will always obey the admissibility conditions:

$$\sum_{j=-\infty}^{\infty} W^2(2^j r) = 1, \quad r \in \left(\frac{3}{4}, \frac{3}{2}\right) \qquad (3)$$

and $\quad \sum_{\ell=-\infty}^{\infty} V^2(t - \ell) = 1, \quad t \in \left(\frac{-1}{2}, \frac{1}{2}\right) \qquad (4)$

For each $j \geq j_0$, frequency window U_j is defined in the Fourier domain by

$$U_j(r,\theta) = 2^{-\frac{3j}{4}} W(2^{-j}r)V\left(\frac{2^{\left[\frac{j}{2}\right]}\theta}{2\pi}\right) \qquad (5)$$

with $U_j(r,\theta) + U_j(r, \theta + \pi)$. Define the waveform $\varphi_j(x)$ by means of its Fourier transform $\varphi_j(\omega) = U_j(\omega)$, where $U_j(\omega_1, \omega_2)$ is the window that defined in the polar coordinate.

$$c(j, \ell, k) = \frac{1}{(2\pi)^2} \int f(\omega)\varphi_{j,\ell,k}(\omega)d\omega =$$
$$\frac{1}{(2\pi)^2} \int f(\omega)U_j(R_{\theta_\ell}\omega)e^{i(x_k,\omega)}d\omega \qquad (6)$$

The low-pass window W_0 can be defined from formula:

$$|W_0(r)|^2 + \sum_{j \geq 0} |W((2^{-j}r)|^2 = 1 \qquad (7)$$

Where $k_1, k_2 \in Z$, define coarse scale curvelet as

$$\varphi_{j_0,k}(x) = \varphi_{j_0,k}(x - 2^{-j_0}k), \qquad (8)$$
$$\varphi_{j_0}(\omega) = 2^{-j_0}W_0(2^{-j_0}|\omega|) \qquad (9)$$

Digital Curvelet Transforms are linear and take as input Cartesian arrays of the form $f[t1, t2]$, $0 \leq t1, t2 < n$, output as a collection of coefficients $c^D(j, \ell, k)$ and

$$c^D(j, \ell, k) = \sum_{0 \leq t_1, t_2 < n} f[t1, t2]\varphi^D_{j,\ell,k}[t_1, t_2], \text{ where}$$
each $\varphi^D_{j,\ell,k}$ is a digital curvelet waveform.

2.3. Gaussian template function

Gaussian template function is an image matrix that described bright in the center and dark outward. The evaluation of the average image value is represented the coefficient μ and the standard deviation is represented σ. Compensative weights ξ have been considered when designing the Gaussian template.

Compensative weights are greater 1 when the color of the images is dark. Conversely, if the image is bright, compensative weights are less than 1.

Increasing the value of compensative weights enhances the overall brightness of the compensated image, due to the increasing the compensative weights make the SV's maximum value significantly increase for the subband coefficient matrices. Reducing the compensative weights results in reducing the brightness of the entire image. Performing the brightness reduction of entire image is beneficial for images with strong light intensity.

Based on analysis and observation of the face database CMU-PIE, FERET; face images will be divided into three categories: dark, bright, and normal.

+ Gaussian template with mean $\mu = 210$ and standard deviation $= \sqrt{32}$, (Ga $(210, \sqrt{32})$) is used for dark category.

+ Gaussian template with mean $\mu = 160$ and standard deviation $= \sqrt{32}$, (Ga $(160, \sqrt{32})$) is used for normal category.

+ Gaussian template with mean $\mu = 100$ and standard deviation $= \sqrt{32}$, (Ga $(100, \sqrt{32})$) is used for bright category.

Three types of face images with corresponding Gaussian template are shown in the Figure 1, and they show the automatic adjustment of all color channels. In addition, the images use an Adaptive Singular Value Decomposition method in the wavelet domain (Adaptive Singular Value Decomposition wavelet ASVDW) for representing the almost normal distribution of bright levels. Images are more clearly and naturally after applicating of brightness compensation method, as if they were taken under normal lighting conditions

2.4. Proposed algorithm use SVD combines with Curvelet transform.

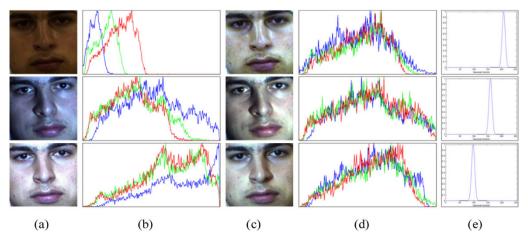Algorithm is performed following below steps:

Fig. 1. (a) Original color images are taken from the CMU-PIE database. (b) Gray level histograms of 1a. (c) Obtained image after applicating of the ASVDW method. (d) Gray level histograms of 1c. (e) The corresponding
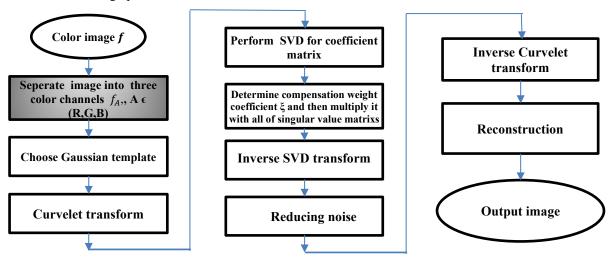
Gaussian function graphs.

Fig. 2. The block diagram of the combination algorithm between SVD and Curvelet transform

Fig. 3. Faces images in FERET image database

Step 1: Read color image (A)

Step 2: Separate color image (A) into three color channels f_A, $A \in (R,G,B)$

Step 3: Choose Gaussian template

Step 4: Perform the Curvelet transform for three color channels f_A and Gaussian template. Calculate the average value of the coefficient matrix C_1 of three-color channels (size $C_1 = M \times N$)

$$\mu_{C1-A} = \frac{1}{M \times N} \times \sum_M^1 \sum_N^1 C_{1-A} \quad , A \in R, G, B \qquad (10)$$

Step 5: Perform the SVD transform for coefficient matrix of Curvelet and Gaussian template.

$$f_A = u.s.v^T \qquad (11)$$

$$Ga = U.S.V^T \qquad (12)$$

Step 6: Determine compensation weight coefficient ξ and then multiply it with all singular value matrix.

$$\xi = \sqrt{\frac{\max(\mu_{C1})}{\mu_{C1-A}} \times \frac{\max(S(Ga))}{\max(s(f_A))}} \qquad (13)$$

$$s' = \xi \times s$$

Step 7: Inversing the SVD transform for frequency subbands. $f_A' = u .s'.v^T$ \qquad (14)

Step 8: Reducing noise at highest detail coefficient matrix with condition:

$$C_{i,j} = \begin{cases} C_{i,j} \; ; \; C_{i,j} > 0 \\ 0 \; ; \; C_{i,j} < 0 \end{cases}$$

(15)

Step 9: Inversing the Curvelet transform for three color channels of image

Step 10: Perform the image reconstruction

Step 11: Output image

The block diagram of the proposed algorithm is presented in the Fig.2.

3. Results and discussion

We implement test the proposed algorithm, Global Adaptive Singular Value Decomposition in Fourier domain algorithm (GASVD_F), Adaptive Singular Value Decomposition in the Wavelet

domain algorithm (ASVD_W) with FERET and CMU_PIE facial image databases. For each of facial image database, we have tested 300 images.

After testing image databases with three algorithms, image databases will be applied PCA algorithm [15] to find out the recognized images. The tested results of up to 300 images in the FERET image database set with three algorithms are shown in Figure 3, Figure 4, Figure 5, and Figure 6.

The tested results of each of algorithm are compared with together via the recognition rate criteria as shown in Tab.1.

As shown in the Table 1, we can see that the recognition rate of the three algorithms with 20 images are the same. However, increasing the number of images (50, 100 and 300), the face recognition rate of the proposed algorithm is the highest.

This demonstrates the outstanding advantages of the proposed algorithm. The tested results of up to 1800 images in the FERET image database set with three algorithms are shown in Figure 7, Figure 8, Figure 9 and Figure 10 and Table 2.

Fig. 4. Faces images after applying the GASVD_F algorithm

Fig. 5. Faces images after applying the ASVD_W algorithm

Fig. 6. Faces images after applying the proposed algorithm

Table 1. Comparison the face recognition rate of three algorithms using 300 images in FERET image database set.

	Algorithm	FERET image database				
		The number of images				
		20	50	100	200	300
Recognition rate RR (%)	GASVD_F	100	91.2	82.8	71.25	58.23
	ASVD_W	100	91.6	83.5	72.75	60.2

	Proposed	100	97.8	97	84.25	64.43

Fig. 7. Faces images in CMU_PIE image database

Fig. 8. Faces images after applying the GASVD_F algorithm

Fig. 9. Faces images after applying the ASVD_W algorithm

Fig. 10. Faces images after applying the proposed algorithm

Table 2. Comparison face recognition rate of three algorithms using 300 images in CMU_PIE image database

	Algorithm	CMU_PIE image database			
		The number of images			
		180	**450**	**900**	**1800**
Recognition rate RR (%)	GASVD_F	97.17	95.1	93.17	92.95
	ASVD_W	97.5	94.83	94	93.67
	Proposed	**97.67**	**96.17**	**94.3**	**94.5**

As shown in table 2, we also see that the recognition rate of the proposed algorithms is higher than two other algorithms with the same number of images. This confirms the advantages of the proposed algorithm via the recognition rate criterion.

4. Center Processing Unit (CPU) Time for Different Image sizes.

In this section, we discuss the efficiency of the proposed method that was determined by measuring the CPU time for different image sizes. When the image size is large, it takes a long time to calculate. But, the image size used for face recognition is not typically large, so, the calculation could be determined quickly with the high speed processing CPU. The proposed method was performed with Microsoft Visual C++ 2010. The experiments were conducted on a laptop with Intel Core i3-7100, 8GB RAM, Windows 10 pro 64 bit. The results are shown in the table 3, and they also show that the efficiency of the proposed method for recognizing a face in a short time.

Table 3. Computational time with different Image sizes

Method/size of Image	CPU time (second/Image)		
	64x64	128x128	256x256
GASVD_F	0.055	0.229	1.229
ASVD_W	0.068	0.237	1.639
Proposed	0.146	0.298	1.372

5. Conclusion

Lighting variations are still a challenge in face recognition. To overcome this problem, there are some novel algorithms are proposed such as Global Adaptive Singular Value Decomposition in the Fourier domain algorithm (GASVD_F) and Adaptive Singular Value Decomposition in the Wavelet domain algorithm (ASVD_W). These methods show high performance for the face matching task and are highly useful for face detection. We proposed another method to overcome light variation in face recognition. With the tested results of three algorithms with CMU-PIE and FERET color image databases via recognition rate criterion (RR) show that the proposed algorithm shows the recognition rate is highest when perform face images recognition with different number of images. The results are shown in Table 1 and Table 2. These results shown the effectiveness of the proposed algorithm.

References

[1] A Baradarani, QMJ Wu, M Ahmadi, An efficient illumination invariant face recognition framework via illumination enhancement and DD-DTCWT filtering Elsevier, Pattern Recognition, Vol 46, 2013, pp (57-72).

[2] X.Cao, W.Shen, L.G.Yu, Y.L.Wang, J.Y.Yang, Z.W.Zhang, Illumination invariant extraction for face recognition using neighboring wavelet coefficients. Elsevier, Pattern Recognition Vol. 45, 2012, pp. (1299-1305).

[3] HaifengHu, Variable lighting face recognition using discrete wavelet transform. Elsevier, Pattern Recognition Letters, Vol. 32, 2011, pp. (1526-1534)

[4] Marios Savvides and B.V.K. Vijaya Kumar, Illumination normalization using logarithm transforms for face authentication. AVBPA, Springer, 2003, pp. (549-556)

[5] Shan Du, R. Ward, Wavelet-based illumination normalization for face recognition. IEEE International Conference on Image Processing 2005. doi:10.1109/icip.2005.1530215

[6] Jing-Wein Wang, Ngoc Tuyen Le, Jiann-Shu Lee, Chou-Chen Wang, Color face image enhancement using adaptive singular value decomposition in Fourier domain for face recognition. Elsevier, Pattern Recognition, Volume 57, 2016, pp. (31-49)

[7] H. Han, S. Shan, X. Chen, and W. Gao, A comparative study on illumination preprocessing in face recognition, Pattern Recognition, vol. 46, 2013, pp. (1691-1699).

[8] Y. Adini, Y. Moses, and S. Ullman, Face recognition: the problem of compensating for changes in illumination direction,. IEEE Trans. Pattern Anal., vol. 19, 1997, pp. (721-732).

[9] W. Chen, M. J. Er, and S. Wu, Illumination compensation and normalization for robust face recognition using discrete cosine transform in logarithm domain, IEEE Trans. System, Man, and Cyber., vol. 36, 2006, pp. (458-466)

[10] H. Demirel and G. Anbarjafari, Pose invariant face recognition using probability distribution functions in different color channels,. IEEE Signal Process. Letters, vol. 15, 2008, pp. (537-540).

[11] J.W.Wang, J.S. Lee, and W.Y. Chen, Face recognition based on projected color space with lighting compensation. IEEE Signal Processing Letters, vol. 18, 2011, pp. (567-570)

[12] J.W.Wang, Ngoc Tuyen Le, Jiann-Shu Lee, C.C.Wang, Illumination compensation for face recognition using Adaptive Singular Value Decomposition in the Wavelet domain. Elsevier, Information Sciences, Vol 435 (2018), pp (69-93).

[13] Satonkar Suhas S., Kurhe Ajay B., Dr. Khanale Prakash B. Face Recognition Using Singular Value Decomposition of Facial Colour Image Database International Journal of Science and Research (IJSR), ISSN (Online): 2319-7064, Vol. 4, Issue 1, 2015, pp (249-254)

[14] E.Candes, L.Demanet, David Donoho and Lexing Ying, Fast Discrete Curvelet transforms Society for Industrial and applied mathematics Journal, Vol. 5, No. 3, 2006, pp. (861-899)

[15] http://www.cs.otago.ac.nz