Proceedings of the International MultiConference of Engineers and Computer Scientists 2011 Vol I,
IMECS 2011, March 16 - 18, 2011, Hong Kong

A Multi-scale TVQI-based Illumination Normalization Model

YanFeng Sun, JiaWen Liu, LiChun Wang

Abstract—**Face recognition under varying illumination conditions is an unsolved problem. Illumination normalization method is a common preprocessing method for this problem. One of the most popular illumination normalization methods is Total Variation based Quotient Image (TVQI) model. However, only the illumination invariant information in the small-scale part of image is used in TVQI model; therefore, the information is very limited. In this paper, a Multi-scale Fusion TV-based Illumination Normalized (MFTVIN) model is proposed to resolve the problem. Firstly, it uses Multi-scale Splice TVQI model (MSTVQI) to generate the small-scale part. This model is based on TVQI model, and it can generate the illumination invariant small-scale part which contains more detailed information than TVQI model. Secondly, TV-L2 model is used to get the noiseless large-scale part of human face. The large-scale part contains the contour of human face and the shade information. Illumination effects in the large-scale part are removed by region-based histogram equalization and homomorphic filtering. Lastly, two parts are fused to generate the illumination invariant face sample. MFTVIN model do not need the information about the lighting source and training set. Experimental results on some famous face databases prove that the processed image by our model could largely improve the recognition performances under low-level lighting conditions.**

Index Terms—**face recognition, multi-scale fusion, TVQI**

I. INTRODUCTION

In recent years, face recognition has received much attention, and major advances have occurred. However, the performance of most existing face recognition methods is highly sensitive to illumination variation. It will be seriously degraded if the faces under variable lighting. Thus, illumination is one of the factors affecting the recognition performance significantly. And because natural illumination is beyond the control of man-made, the light conditions of most face recognition methods are limited. Within the past decade, many methods have been proposed for the illumination problem. In general, these methods can be divided into three main categories:

- Methods based on the traditional image processing technique. For instance, histogram equalization [1-2] and logarithm transform [3] are widely used for illumination normalization. However, it is difficult for these image processing techniques to handle the different lighting conditions.
- Methods based on constructing 3-D face model. For example, illumination cone [4-5] can be approximated well by low-dimensional linear subspace whose basis vectors are estimated from training data using the generative model. The spherical harmonic [6-7] model is applied to represent the low-dimensional subspace of different illumination face images. However, these methods based on 3-D model either require the assumptions of light source or need many training samples, which are not practical for real applications.
- Methods based on extracting illumination invariant features. For instance, Retinex model [8], multi-scale Retinex model [9] and Self-Quotient Image (SQI) model[10-11] are proposed to deal with the illumination problem. In SQI model, the illumination invariant is obtained by division over a smoothed version of the image itself. These methods have received much attention recently. Total Variation based quotient image (TVQI) model [12-13] is one of the most popular methods.

Total Variation based Quotient Image (TVQI) model combines the TV-L1 decomposition model with the SQI model. TV-L1 model is an anisotropic diffused partial differential equation (PDE) and it has the scale-selecting property. It could preserve the edge information in image. In [11], Wang et al. proposed SQI model which is based on the basic conception of quotient image. SQI method neither uses the information about the lighting source, nor needs a training set. It directly extracts the illumination invariant face features. TVQI model uses TV-L1 decomposition model to get the low-frequency part of face sample, and then utilizes the SQI model to generate an illumination invariant small-scale image.

In this paper, we propose an illumination insensitive measure extraction method for face recognition under varying lighting called Multi-scale Fusion TV-based Illumination Normalized (MFTVIN) model. The main idea of MFTVIN model consists of two parts. Firstly, we propose a improved model of TVQI called Multi-scale Splice TVQI (MSTVQI) model. MSTVQI model divides face sample into

Manuscript received December 27, 2010. This paper is supported by the National Key Basic Research Program of China (973 Program) (No. 2011CB302703）, NSFC (No. 60973057,U0935004) and BJNSF（4112008）.

Yanfeng Sun is with Beijing Key Laboratory of Multimedia and Intelligent Software Technology , College Of Computer Science and Technology , Beijing University Of Technology , Beijing. 100124, China (emails: yfsun@bjut.edu.cn).

Jiawen Liu is with Beijing Key Laboratory of Multimedia and Intelligent Software Technology , College Of Computer Science and Technology , Beijing University Of Technology , Beijing. 100124, China ((phone: 010-67396568-2310; emails: liujiawen26@sohu.com).

Lichun Wang is with Beijing Key Laboratory of Multimedia and Intelligent Software Technology , College Of Computer Science and Technology , Beijing University Of Technology , Beijing. 100124, China (emails: wanglc@bjut.edu.cn).

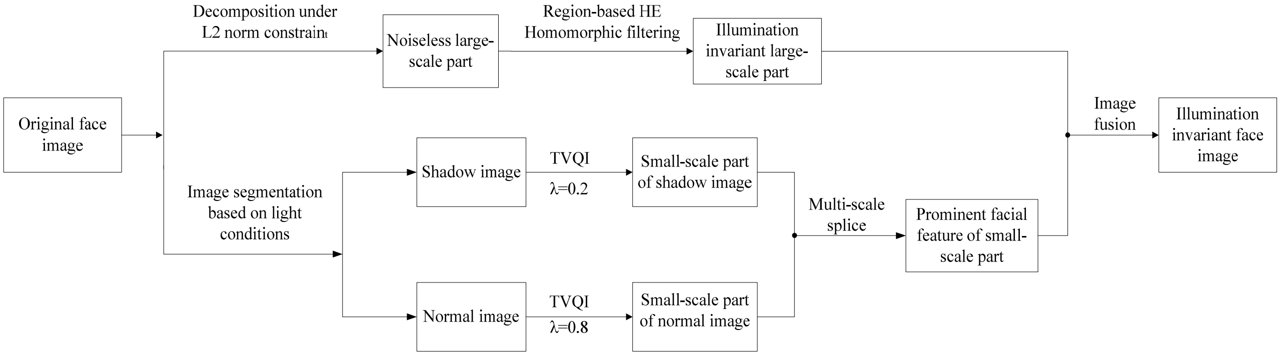

Fig. 1. Processing procedure of MFTVIN

two areas: the shadow area and the normal area. And then it applies the TVQI model with different λ_{L1} on the two areas respectively to generate a small-scale part that contains more detailed information. Secondly, it utilizes TV-L2 model to generate a noiseless large-scale part, and then the illumination effects in this part are compensated by using region-based histogram equalization and homomorphic filtering. The gray level contrast is enhanced by the two steps the noiseless large-scale part. At last, the illumination normalized facial features in two scale parts are fused. In order to prove the face sample pre-processed by MFTVIN is robust to lighting, the experiments were conducted on Yale Face Database B [4], CMU PIE [14] and CAS-PEAL [15] Face Database. According to the experiments, the processed result of MFTVIN is illumination invariant. Using this information to assist face recognition could improve the performance of subspace approaches under low-level lighting condition.

II. Multi-scale Fusion TV-based Illumination Normalized model

In this paper a Multi-scale Fusion TV-based Illumination Normalized (MFTVIN) model is proposed for face recognition under varied lighting conditions. It can be used to remove the illumination effects of face image, and improve the face recognition performance. The whole processing procedure of MFTVIN model is shown in Fig. 1, and the detailed analysis is given in this section.

A. Total Variation based Quotient Image (TVQI) Model

TVQI model can achieve good performance, when it used for face recognition under varying illumination conditions. The main idea of this model consists of two parts: SQI model and TV-L1 model. SQI model is a preprocessing method for face recognition. This model can generate an illumination invariant face image from a single face sample. This model uses the low-frequency part which represents the illumination effects of face image to compose the original image, and then generates the illumination invariant features. However, the weighted Gaussian filter they used has trouble keeping sharp edges in low frequency illumination fields, and the parameter selection is empirical and complicated. In order to overcome these limitations, Chen et al. in [13] proposed to utilize the TVQI model to factorize an image, and then obtain illumination invariant. TVQI model generates the large-scale part of face image by utilizing edge-preserving capability of the TV-L1 [16] model. Utilizing the large-scale part and the original image, the TVQI model generates the small-scale part by using SQI model. In TVQI model, the small-scale part is defined as:

$$\tilde{u} = \arg\min_u \int |\nabla u| dx + \lambda_{L1} \int | I - u | dx \qquad (1)$$

$$TVQI = v' = I / \tilde{u} \qquad (2)$$

Where v' is the small-scale part. u denotes the large-scale part of the original image I, and $\tilde{u}$ is the Stationary solution of large-scale u. ∇ is the gradient operator. λ_{L1} is the parameter.

B. Multi-scale Splice TVQI Model

For face recognition, the main difference between two persons is detailed facial features, such as the eyebrow, eyes and nose shapes. So the small-scale part containing the detailed information is very important for face recognition. We propose a new method called Multi-scale Splice TVQI (MSTVQI) model. This model can generate the illumination invariant small-scale part which contains more detailed information than TVQI model. The processing procedure of MSTVQI model is shown in Fig. 2.

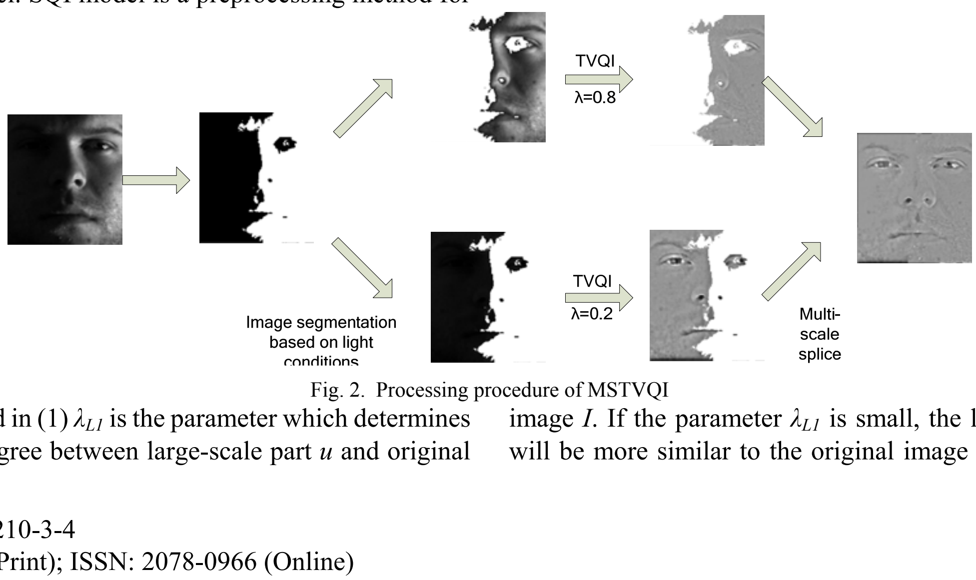

Fig. 2. Processing procedure of MSTVQI

It can be found in (1) λ_{L1} is the parameter which determines the similarity degree between large-scale part u and original image I. If the parameter λ_{L1} is small, the large-scale part u will be more similar to the original image I for minimizing

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

the functional in (1). So the large-scale part u is denoised more obviously. Whereas when λ_{L1} is large, the large-scale part is denoised less obviously. And then it can be proved in (2) that the boundary in face image is left in small-scale part. So when the large-scale part u is more similar to the original image I, the small-scale part v' can contain more boundary information. Thus, the small-scale part can contain more detailed information, when λ_{L1} selects a small value; whereas the small-scale part can contain less detailed information When λ_{L1} selects a large value.

The detailed information of face image plays a decisive role in face recognition under low-level lighting condition. The recognition performance will be better, if the detailed information can be extracted more. However, the performance is not good when the value of λ_{L1} is selected as less as possible. In [13], Chen et al proved that the recognition rate will decreased when the value is lower than a certain value. In TVQI model, the scale parameter λ_{L1} is determined by the size of sample image. The value of λ_{L1} is fixed for a given size of face image (the value of λ_{L1} for size of image is 100×100: 0.7 to 0.8).

In MSTVQI model, the face image is divided into two areas by illumination conditions. In this paper, the method for dividing the image exactly is not the research focus in this paper. A simple method that uses the average gray value is used in our model. The gray value of each pixel point is compared with the average gray value of the face image. When the gray value of a pixel is lower than the average gray value, the pixel belongs to shadow area. Whereas the pixel belongs to normal area when the gray value of a pixel is higher than the average gray value.

$$flag(x,y)=\begin{cases}1 & if \quad I(x,y)>aver\\ 0 & if \quad I(x,y)\le aver\end{cases} \qquad (3)$$

$$aver=(\sum_{i}^{n}\sum_{j}^{m}I(i,j))/(m*n)$$

Where m and n denote the length and width of the image. $aver$ is the average gray value of the image. When $flag(x,y)$ is equal to 1, the pixel belongs to the normal area. And when $flag(x,y)$ is equal to 0, the pixel belongs to shadow area.

In MSTVQI model, it applies TVQI model with different λ_{L1} on different areas respectively to generate a small-scale part of image which contains more detailed features. The pixels of shadow area apply the TVQI model with a smaller value of λ_{L1} for extracting more detailed information, and the pixels of normal area apply the TVQI model with a higher value of λ_{L1} for extracting detailed information without additional noise. In this paper, size of images in the experiments are normalized into 100×100. Thus, λ_{L1} is equal to 0.8 in normal area, and λ_{L1} is equal to 0.2 in shadow area in this model. The results of MSTVQI model are compared with the results of TVQI in Fig. 3 It can be found the results of MSTVQI model contain more detailed information than the results of TVQI. Then it will be proved in section 4 by experiments.

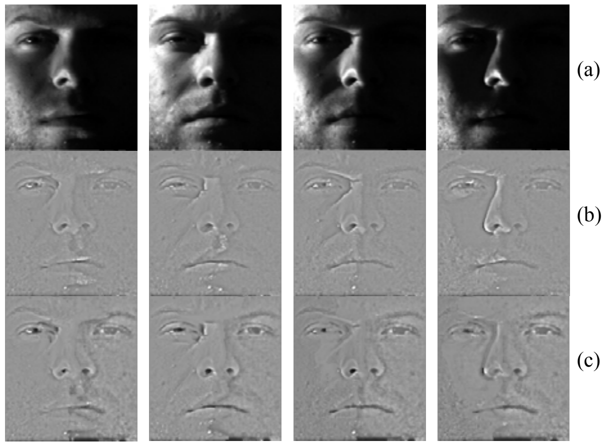

Fig. 3. Comparison between the results of TVQI and the results of MSTVQI (a) the original images (b) the results of TVQI (c) the results of MSTVQI

C. Illumination Normalization In the Large-scale Part

The information contained in the small-scale part is limited, because the small-scale part only contains the detailed facial features, like the eyebrow, eyes, nose, and mouth shapes. So it is necessary to combine more illumination invariant information for improving recognition performance. The contour and the shade information of human face contained in the large-scale part are useful for face recognition. However, the large-scale part contains not only these useful features but also the illumination effects. So the features in large-scale part should be processed to remove the illumination effect.

In [17], Gaoyun An et al. analyzed the difference between the TV-L1 model and TV-L2 model, and proved the TV-L2 model is more suitable than the TV-L1 model for generating the large-scale part. So the TV-L2 model is used in this paper:

$$\tilde{u}=\arg\min_{u}\int|\nabla u|dx+\lambda_{L2}\int(I-u)^{2}dx \qquad (4)$$

Where u denotes the large-scale part of the original image I, and ũ is the Stationary solution of large-scale u. ∇ is the gradient operator. λ_{L2} is the parameter. λ_{L2} is different with λ_{L1}. If λ_{L2} is large, more image information is contained in the large-scale part. To keep more information in large-scale part ũ, $\lambda_{L2}=1$ is used in the TV-L2 model.

The whole processing procedure of removing the illumination effect from large-scale part is shown in Fig. 4.

1) Region-based histogram equalization

Histogram equalization (HE) is a simple and effective image processing method. It uses the cumulative function of the gray value to enhance the contrast. But HE is a global transforming method, and it processes based on the whole image information. It often fails to normalize the spurious illumination effects in image. In [18], Jobson et al. proposed Region-based HE to compensate the illumination effect based on local regions. In [19], Shan et al. already proved that using complex region partition method is time-consuming and not practical. In [17], Gaoyun An et al. proved Region-based HE can remove the illumination effect from large-scale part well. Therefore, the face region is roughly segmented into four parts in this paper.

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

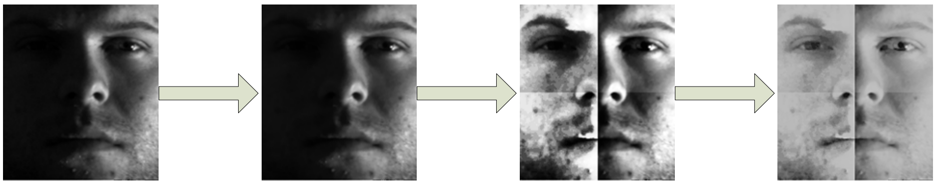

Fig. 4. Processing procedure of removing the illumination effect from large-scale part

2) *Homomorphic filtering*

Homomorphic filtering is very well known as a way for image dynamic range and increasing contrast, it is used to correct non uniform illumination and to enhance contrasts in the image. An image of an object might be modeled as: $f(x,y)=i(x,y)*r(x,y)$, where $i(x,y)$ and $r(x,y)$ are the illuminance and reflectance of the object. In this case, some way of converting multiplication into addition must be employed before trying to apply Fourier filtering. The obvious way to do this is to take logarithms of both sides. The illuminance and reflectance of the image can be separated linearly in the frequency domain by taking the logarithm of the image intensity. To make the illumination of an image more even, the high-frequency components are increased and low-frequency components are decreased, because the high-frequency components are assumed to represent mostly the reflectance, whereas the low-frequency components are assumed to represent mostly the illumination. That is, high-pass filtering is used to suppress low frequencies and amplify high frequencies, in the log-intensity domain.

Region-based HE is more effective than HE, but it still has some disadvantages of HE:

- In the transformation, some detailed information of the image may be weakened because of the reduction of the gray-scale.
- Under low-level lighting conditions, the transformation may over-enhance the image contrast, and then it brings image distortion.

Homomorphic filtering can make the image gray value in a certain extent, so it can ease the over-enhanced image contrast. At the same time, it also can enhance the weakened detailed information by extracting the high-frequency components. So homomorphic filtering can overcome the disadvantages of Region-based HE to improve the recognition performances under low-level lighting conditions.

D. Multi-scale Fusion

The result of MSTVQI model and the processed large-scale part combined to generate a final illumination invariant face sample. The fusion model is:

$$\mathbf{y} = \alpha u \oplus \beta v \tag{5}$$

where $\oplus$ is a fusion operator, α and β are two fusion factors, u is the processed large-scale part, v is the result of MSTVQI model. Here we just choose a simple fusion method: $\oplus$ is chosen as a plus operator and $\alpha = 0.6$, $\beta = 0.4$. Only the information about detailed features is contained in v , and the information is limited. Therefore, it plays α less important part in the final illumination invariant image, and $\alpha > \beta$. Using more complicated fusion methods, such as the fuzzy logical method or the self-adaptive method, could achieve a better processing result. In this paper, only the simple weighted average fusion method is used.

III. Experiments

The well-known TVQI model achieves good performance in face recognition under low-level lighting conditions; therefore, it is used to compare with our methods. Because the dimension of these normalized face samples are too high, the processed images can not be used in face recognition. Therefore, subspace approaches are used for face recognition. The methods in this paper can combine with all kinds of subspace approaches as pre-processing methods. In this paper, we apply PCA to perform subspace approaches on processed images in this paper. Because the scale parameter λ_{L1} is determined by the size of sample image in TVQI model, all images in experiments are cropped and resized to 100×100. The performances of different pre-processing methods used in famous face databases, including the Yale Face Database B, the CMU PIE and the CAS-PEAL face database, are all illustrated in this section.

A. Experiment on the Yale Face Database B

The Yale face database B contains images of ten individuals with nine poses and 64 illuminations per pose. The frontal face images of all subjects, each with 64 different illuminations are used for evaluation. They are divided into five subsets based on the angle of the light source directions. The five subsets are: subset 1 (0º to 20º), subset 2 (21º to 40º), subset 3 (41º to 65º), subset 4 (66º to 80º), subset 5 (above 81º). As a result, there are total 640 images: 140, 100, 120, 100, and 180 images in subset 1 to 5, respectively. Fig. 5 shows five images for one subject from different subsets and the corresponding results of MFTVIN model.

Fig. 5. Five images (from left to right) of one subject from subset 1 to 5, respectively (first row), and the corresponding results of MFTVIN (second row).

TABLE I. RECOGNITION RATE(%) COMPARISON ON YALE DATABASE B

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Subset	2	3	4	5
PCA	95.9184	65.5172	32.0	12.8492
TVQI+PCA	100	98.2759	100	93.8547
MSTVQI+PCA	100	100	100	98.8827
MFTVIN +PCA	100	100	100	99.4413

This experiment is devised to use the subset 1 as training set, the other images from subset 2 to 5 as testing set. Table I shows that the recognition results of different methods. As can be seen, MFTVIN and MSTVQI outperform TVQI method on all subsets, and MFTVIN has better performance than MSTVQI. If the accuracy rates are considered, MSTVQI method improves the performance of TVQI by 5.028% for the subset 5 with the extremely lighting conditions; MFTVIN method improves the performance by 5.5866%. It can be proved that the results of MSTVQI model contain more detailed information than the results of TVQI. So the results of MSTVQI should be used in MFTVIN as the small-scale part. And it is clear that the method of using different scale part of image can improve the performance effectively.

B. Experiment on the CMU PIE Face Database

To further prove the validity of our methods, some experiments on the CMU PIE face database are given. The CMU PIE face database contains 68 subjects with 41368 face images as a whole. The face images were captured by 13 synchronized cameras and 21 flashes, under variations in pose, illumination and expression. Our work here concerns about illumination variations rather than pose and expression. So illumination subset was used in our experiment. There are 21 distinct sources of lights used to illuminate the face. We use 68 subjects with 1428 face images, each with 21 different illuminations for testing. One experiment is conducted on this database. We use 4 images per subject as the training set, the other images as testing set.

TABLE II. RECOGNITION RATE(%) COMPARISON ON CMU PIE FACE DATABASE

	PCA	**TVQI +PCA**	**MSTVQI +PCA**	**MFTVIN +PCA**
Recognition rate	44.4706	89.8824	94.1176	99.0588

Table II illustrates the recognition rate of various approaches for the CMU PIE database. As can be seen, MFTVIN achieves closely to 100% recognition rate, and MSTVQI can reach 94% recognition rate. MSTVQI method improves the performance of TVQI by 4.2352%; MFTVIN method improves the performance by 9.1764%. Therefore, it is clear that MFTVIN outperforms other methods.

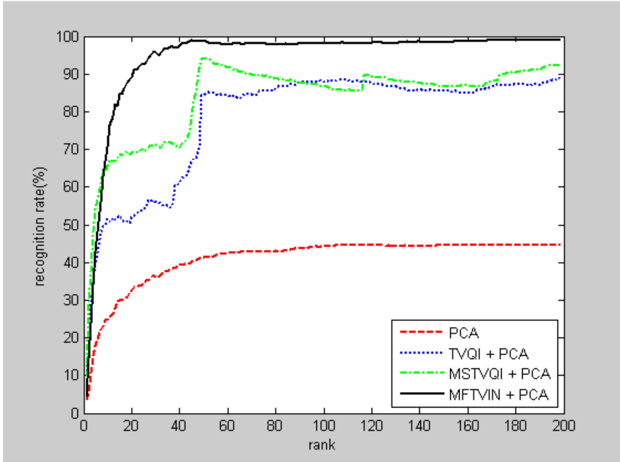

Fig. 6. Accuracy recognition rates at rank 1–200 of various approaches in CMU PIE face database

The recognition rates at rank 1–200 in CMU PIE face database are illustrated in Fig. 6. Rank means the number of features. From the Fig. 6, it is proved the recognition rates will rise among rank 1–50, then they may reach some maximum recognition rates among rank 50–200. When rank is above 20, the recognition rates of MFTVIN and MSTVQI increased greatly. And the maximum recognition rate of MFTVIN model can be up to 99% among rank 50–100. It could be noticed that the recognition rate of MFTVIN is highest for different ranks.

C. Experiment on the CAS-PEAL Face Database

Lastly, the experiments on the CAS-PEAL face database are given. The CAS-PEAL face database contains 30,864 images of 1040 subjects. They are with varied pose, expression, accessory and lighting. In this experiment, the frontal face images of 22 subjects, each with 20 different illuminations are used for evaluation. We use 10 images per subject as the training set, the other images as testing set. The recognition results are shown in Table III, and the recognition rates at rank 1–100 in CAS-PEAL face database are illustrated in Fig. 7.

TABLE III. PERFORMANCE COMPARISON ON CAS-PEAL FACE DATABASE

	PCA	**TVQI +PCA**	**MSTVQI +PCA**	**MFTVIN +PCA**
Recognition rate	39.0909	35.4545	42.7273	49.0909

ISBN: 978-988-18210-3-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

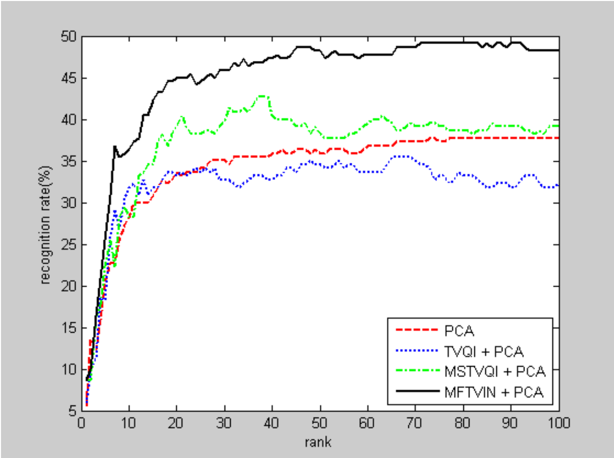

Fig. 7. Accuracy recognition rates at rank 1–200 of various approaches in CAS-PEAL face database

Table III illustrates the recognition rate of various approaches for the CAS-PEAL database. If the accuracy rates are considered, MSTVQI method improves the performance of TVQI by 7.2728%; MFTVIN method improves the performance by13.6364%.Because the images in CAS-PEAL database have some slight change of expression an distance, the performance of TVQI is worse than PCA. But MSTVQI and MFTVIN still achieves good performances. From the Fig.7, it is seen the recognition rate of MFTVIN outperforms other methods for different ranks.

IV. Conclusion

In this paper, a Multi-scale Fusion TV-based Illumination Normalized (MFTVIN) model is proposed for the pre-processing of face recognition under varied lighting conditions. It can be applied to face recognition with only one sample per subject employing subspace approaches. It uses MSTVQI model to generate an illumination invariant small-scale image. This model divide face sample into two areas, and then it applies the TVQI model with different λ_{L1} on the two areas respectively It generates a noiseless large-scale part using TV-L2 model, and then removes the illumination effect by using region-based HE and homomorphic filtering. At last it combines two scaled parts by fusion methods. According to the experiments on the well-known the Yale Face Database B, the CMU PIE and the CAS-PEAL face database, MFTVIN model is an effective method for illumination problem in face recognition, and robust to different lighting and noise.

Acknowledgment

I would like to take this chance to express my sincere gratitude to my supervisors, Yanfeng Sun and Lichun Wang, who are professors of Beijing University Of Technology, for their kindly assistance and valuable suggestions during the process of my thesis writing. My gratitude also extends to all the teachers who taught me during my graduate years for their kind encouragement and patient instructions. Last, I would like to offer my particular thanks to my friends and family, for their encouragement and support for the completion of this thesis.

References

[1] S. M. Pizer and E. P. Amburn, “Adaptive histogram equalization and its variations,” Comput. Vis. Graph., Image Process., vol. 39, no. 3, pp. 355–368, 1987.

[2] S. Shan, W. Gao, B. Cao, and D. Zhao, “Illumination normalization for robust face recognition against varying lighting conditions,” in Proc. IEEE Workshop on AMFG, 2003, pp. 157–164.

[3] M. Savvides and V. Kumar, “Illumination normalization using logarithm transforms for face authentication,” in Proc. IAPR AVBPA, 2003, pp. 549–556.

[4] A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman, “From few to many: Generative models for recognition under variable pose and illumination,” in Proc. 4th IEEE Int. Conf. Automatic Face and Gesture Recognition, 2000, pp. 277–284.

[5] A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman, “From few to many: Illumination cone models for face recognition under variable lighting and pose,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 23, no. 6, pp. 643–660, Jun. 2001.

[6] R. Basri and D. Jacobs, Lambertian Reflectance and Linear Subspaces, NEC Research Inst. Tech. Rep. 2000-172R, 2000, Tech. Rep.

[7] R. Basri and D. W. Jacobs, “Lambertian reflectance and linear subspaces,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 2, pp. 218–233, Feb. 2003.

[8] E. H. Land and J. J. McCann, “Lightness and retinex theory,” J. Opt. Soc. Amer., vol. 61, pp. 1–11, 1971.

[9] D. J. Jobson, Z. Rahman, and G. A. Woodell, “A multi-scale retinex for bridging the gap between color images and the human observation of scenes,” IEEE Trans. Image Process., vol. 6, no. 7, pp. 965–976, Jul. 1997.

[10] H. Wang, S. Z. Li, and Y. Wang, “Generalized quotient image,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2004, pp. 498–505.

[11] H. Wang, S. Z. Li, and Y. Wang, “Face recognition under varying lighting conditions using self quotient image,” in Proc. IEEE Int. Conf. Automatic Face and Gesture Recognition, 2004, pp. 819–824.

[12] T. Chen, W. Yin, X.S. Zhou, D. Comaniciu, T.S. Huang, “Illumination normalization for face recognition and uneven background correction using total variation based image models,” In: Proc. IEEE Internat. Conf. on Computer Vision and Pattern Recognition,2005, vol. 2, pp. 532–539.

[13] T. Chen, W. Yin, X.S. Zhou, D. Comaniciu, T.S. Huang, “Total variation models for variable lighting face recognition,” IEEE Trans. Pattern Anal. Machine Intell., vol. 28, no. 9, pp.1519–1524, 2006.

[14] T. Sim, S. Baker, and M. Bsat, “The CMU pose, illumination, and expression (PIE) database,” in Proc. IEEE Int. Conf. Automatic Face and Gesture Recognition, 2002, pp. 46–51.

[15] W. Gao, B. Cao, S. Shan, D. Zhou, X. Zhang, D. Zhao, “The CAS-PEAL largescale Chinese face database and evaluation protocols,” Technical Report No. JDL_TR_04_FR_001, Joint Research and Development Laboratory, CAS,2004.

[16] T.F. Chan, S. Esedoglu, “Aspects of tatal variation regularized L1 functions approximation,” SIAM Journal on Applied Mathematics, vol. 65, no. 5, pp. 1817~1837, 2005.

[17] G.Y. An, J.Y. Wu, Q.Q. Ruan, “An illumination normalization model for face recognition under varied lighting conditions,” Pattern Recognition Letters, vol. 31, no. 9, pp. 1056-1067, 2010.

[18] D.J. Jobson, Z. Rahman, G.A. Woodell, “Properties and performance of a center/surround retinex,” IEEE Trans. Image Process, vol. 6, no. 3, pp. 451–462, 1997.

[19] S.G. Shan, W. Gao, B. Cao, D. Zhao, “Illumination normalization for robust face recognition against varying lighting conditions,” In: Proc. IEEE Internat. Workshop on Analysis and Modeling of Faces and Gestures (AMFG’03), 2003, pp. 157–164.