

HUMAN FACE VERIFICATION UNDER ILLUMINATION VARIATION

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To

The Honorable Soul of My Father, whose Children's Success was His Only Wish.

To

My Kind Mother

To

My Beloved Wife and Son without their Support and Understanding It Would Have
been Impossible to Achieve Such a Goal

To

The Respected Soul of My Previous Supervisor the Late Prof. Datuk.Dr. Marzuki
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And Last But Not Least, To

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ABSTRACT

The appearance of a face will vary intensely when the illumination changes. The changes in the illumination conditions during image capturing make it difficult to obtain accurate face verification. Changes in illuminations results in two main problems, which are reflections and shadows. One of the most important aspects influencing the verification accuracy is illumination normalization. This thesis explored the use of fusion normalization methods to improve the performance of face verification under illumination variation. It has been shown that a single normalization technique is inadequate to solve the problems of illumination. In this study, several normalization methods such as Discrete Wavelet Transform, Discrete Cosine Transform, and Classified Appearance based Quotient Image were investigated for illumination normalization. A verification process was performed for each normalization technique and the outputs of the process, which were the likeness scores would be fused together to improve the final output. In the verification step, Principal Component Analysis was used to reduce the vector size of image and Linear Discriminant Analysis was used to extract discriminative information. In addition, un-trained fusion methods such as Max-Rule, Min-Rule, and Ave-Rule were used to get a unified decision with a reduced error rate. Besides that, fusion normalization methods were also used to solve all problems caused by illumination. The experiments were done on XM2VTS and Yale database B. The results of this research showed that the efficiency of Ave-Rule technique is better than other methods for XM2VTS, and the best fusion method for Yale database B is Min-Rule. To evaluate the techniques, the results have been compared with the outcomes of the fusion of each pair of the normalization methods as well as the results obtained from using other techniques. The comparison showed that the fusion of the three normalization techniques offered a better performance as compared to the fusion of two illumination normalization methods. Furthermore, the performance of face verification based on the fusion of the normalization methods was better in comparison to a single normalization technique.

ABSTRAK

Keketaraan penampilan wajah akan berbeza apabila wujudnya perubahan pencahayaan. Perubahan pencahayaan dalam merakam imej menyukarkan proses pengesanan muka dengan ketepatan yang baik. Perubahan pencahayaan akan menyebabkan dua masalah utama iaitu pantulan dan bayang-bayang. Normalisasi pencahayaan adalah antara aspek penting yang mempengaruhi kualiti pengesanan. Tesis ini meneroka penggunaan kaedah gabungan normalisasi untuk meningkatkan kualiti pengesanan muka. Kaedah normalisasi tunggal tidak memadai dalam memperbaiki masalah ini secara amnya. Dalam kajian ini, beberapa kaedah normalisasi seperti Pengubah Wavelet Diskret, Pengubah Kosinus Diskret, dan Klasifikasi Rupa – berdasarkan Kadar Imej dianalisis dan digunakan sebagai kaedah normalisasi. Proses pengesanan dijalankan untuk setiap kaedah normalisasi dan proses outputnya adalah skor bandingan yang digabung bersama untuk memperbaiki keseluruhan output. Dalam langkah pengesanan, digunakan Analisis Komponen Utama untuk mengurangkan dimensi vektor maklumat imej, dan Analisis Diskriminasi Linear digunakan untuk mengoptimumkan maklumat diskriminatif. Di samping itu, kaedah gabungan tidak-terlatih seperti Peraturan-Maksima, Peraturan-Minima, dan Peraturan-Purata digunakan untuk mendapatkan keputusan bersatu dengan ralat dikurangkan. Selain itu, kaedah gabungan normalisasi juga digunakan untuk menyelesaikan masalah pencahayaan. Eksperimen telah dijalankan pada XM2VTS dan Pangkalan Data Yale B. Keputusan menunjukkan kaedah Peraturan-Purata adalah terbaik berbanding kaedah lain untuk XM2VTS, dan gabungan Peraturan-Minima adalah terbaik untuk Pangkalan Data Yale B. Keputusan daripada kaedah yang dicadangkan akan dibandingkan dengan setiap kaedah gabungan normalisasi dan beberapa kaedah lain. Kualiti pengesanan dengan gabungan tiga kaedah normalisasi adalah lebih baik berbanding gabungan dua kaedah normalisasi. Di samping itu, pengesanan muka dengan kaedah gabungan normalisasi juga adalah lebih baik berbanding kaedah normalisasi tunggal.

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LIST OF ABBREVIATIONS

<i>HE</i>	-	Histogram Equalization
<i>LBP</i>	-	Local Binary Patterns
<i>WT</i>	-	Wavelet Transforms
<i>SH</i>	-	Spherical Harmonics
<i>QI</i>	-	Quotient Image
<i>DCT</i>	-	Discrete Cosine Transform
<i>HF</i>	-	Homomorphic Filtering
<i>CAQI</i>	-	Classified Appearance-based Quotient Image
<i>FLD</i>	-	Fisher Linear Discriminant
<i>MAP</i>	-	Maximum A Posterior
<i>QIR</i>	-	Quotient Illumination Relighting
<i>GIIS</i>	-	Generic Intrinsic Illumination Subspace
<i>MQI</i>	-	Morphological Quotient Image
<i>PCA</i>	-	Principal Component Analysis
<i>AHE</i>	-	Adaptive Histogram Equalization
<i>BHE</i>	-	Block-based Histogram Equalization
<i>LTP</i>	-	Local Ternary Patterns
<i>LDCT</i>	-	Local Discrete Cosine Transform
<i>DWT</i>	-	Discrete Wavelet Transform
<i>IRM</i>	-	Illumination Reflectance Model
<i>RLI</i>	-	Rule of Lighting Invariance
<i>IVIW</i>	-	Improved Variable Illumination on Wavelet
<i>HMV</i>	-	Homomorphic Vertical filtering
<i>HMH</i>	-	Homomorphic Horizontal filtering
<i>SQI</i>	-	Self-Quotient Image
<i>LDA</i>	-	Linear Discriminant Analysis
<i>EGFC</i>	-	Ensemble based Gabor Fisher Classifier

<i>ANN</i>	-	Artificial Neural Networks
<i>HMM</i>	-	Hidden Markov Models
<i>LEM</i>	-	Line Edge Map
<i>SVM</i>	-	Support Vector Machine
<i>MCS</i>	-	Multiple Classifier Systems
<i>MRF</i>	-	Markov Random Field
<i>FAR</i>	-	False Acceptance Rate
<i>FRR</i>	-	False Rejection Rate
<i>EER</i>	-	Equal Error Rate
<i>HTER</i>	-	Half Total Error Rate
<i>GT</i>	-	Global Threshold

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CHAPTER 1

INTRODUCTION

In this chapter, an introduction to the current study is presented. First, the background of the problem to be solved is explained. After that, the statement of problem, objectives, and scope of study are respectively illustrated.

1.1 Background of the Problem

Face recognition procedure is one of the most prosperous applications of image processing in which people execute adeptly and routinely in their daily lives. Face recognition and face verification are two categories of a face identification system that have acquired noticeable attention from forty years ago. Because of their wide usages in law enforcement, commerce, security, multimedia management and other areas, they have consequentially attracted various areas of research, such as pattern recognition, biometrics, computer vision, machine learning, and computer graphics. In addition, wide accessibility of powerful and low-cost desktop and embedded computing systems have produced a huge interest in automatic images processing in a number of these applications.

A face-identification system automatically identifies faces present in images or videos. Face identification and face verification are two modes of this system. Face identification (or recognition) is a one-to-many comparing processes, which compares a claimed face image , called probe image, against all the template images in a database to specify the identity of the query face. "Face verification is used in order to determine whether an identity claim is false or true. Actually, face

verification is a one-to-one matching procedure which compares a probe image with a stored template face image whose identity is being claimed".

In many of the face verifications applications (Chellappa et al., 1995), the performance and accuracy in controlled environments have now reached a satisfactory level; however, there are still many challenges presented by uncontrolled environments. Some of these challenges are demonstrated by the problems caused by variations in face pose, illumination, and expression. In particular, the effect of variation in the illumination conditions which results in dramatic changes in the face appearance, is one of those challenging problems that a practical face verification faces (Zhao et al., 2003)

Several major problems that are still being addressed by researchers are explained below:

1. **Facial deformation:** Changing the mood, stress, and expressions makes human faces non-rigid and endures deformations. The underlying muscle and tissue structure guides these deformations. They are not arbitrary and it is very difficult to model or analyze these fluctuations from normal images.
2. **Aging:** Appearance of human faces varies due to aging. Faces of various persons age differently depending on habits, stress, health, race, and climate that make the process of verification under aging very difficult.
3. **Cosmetic changes:** In additional natural variations, makeup, surgery, growing or shaving facial hair can deliberately change the face appearance. Sometimes human face verification or recognition across this problem is difficult.
4. **Occlusion:** When another object occludes a part of human face, occlusion will happen.

5. **Pose variation:** In this problem, the similar face seems variously when the viewing condition is changed. Human face recognition and verification under changing pose is very difficult.

6. **Illumination variation:** In this problem, alike face appears variously due to vary lighting condition. More specifically, the variations by illumination could be bigger than the variation among persons. The consequences of prior researches show that important illumination changes cause dramatic variations in the production coefficient vectors, and hence can seriously decrease the performance of face identification.

Recently, many researchers have focused on robust face recognition and verification under pose, expression and illumination variations. The appearance of a face will extremely change when the lighting condition varies. In unnatural illumination conditions of image capturing, the face verification process is very hard. Illumination problem appears where the similar face occurs variously caused by illumination variation. Changes in lighting conditions make face authentication an even more challenging and hard process. Moreover, variation in appearance due to change in the lighting conditions significantly influence the face identification performance. "In order to illustrate a variation of facial appearances produced by illumination, the appearances are sorted into two principal categories: reflections, shadows. Diffuse reflection and specular reflection are two parts of reflection, which have quite different characters and also cast shadow and attached shadow, are two subparts of shadow category" (Nishiyama and Yamaguchi, 2006).

Image capture, face detection and location, face alignment and normalization, feature extraction, face matching and score generation, and decision are six modules of a complete face verification system (Short, 2006).

1. **Image capture:** A claimed image is captured with a digital camera. This image is called probe image. The substance of the probe image

is decided by the position of the person relative to the camera, the expression, poses of the claimant and the changing lighting conditions of the image capture.

2. **Face detection and Location:** A probe image contains the face of a person and a potentially cluttered background scene. In the detection step, the position of the face in the image is detected.
3. **Face alignment and normalization:** In this step, the position and size of each detected face are appraised. A normalization procedure includes Geometric and Photometric parts. Since the size of facial image within the input image varies with the distance between person and camera, geometrical normalization is needed. Thus, the face should be cropped from the image and geometrically changed to a pre-determined fixed size. The photometric compensation is used to eliminate unwanted lighting effects from the probe image. In some cases, the photometrical normalization process can be done before, or before and after the geometric normalization procedure, also it can occur in the past, or before and after the detection process.
4. **Feature extraction:** The efficient information, which is applicable for identifying faces of different persons, is supplied in this step.
5. **Face matching and score generation:** The feature vectors of compensated image are then compared with one or more claimed images, which are in a gallery. This comparison process generates a score, showing how well the probe image matches the gallery.
6. **Decision:** In order to determine the probe is accepted or rejected, the score is compared with a threshold.

1.2 Statement of the Problem

Several different studies on face verification under illumination variation tried to define proper platforms for compensation of influence for varying lighting on face verification and recognition. It has been shown experimentally and theoretically that differences in appearance caused by illumination are bigger than differences between individuals. Various approaches have been suggested to overcome illumination problem but in the majority of them, only controlled condition was considered. However, it is important to consider uncontrolled conditions to emulate the actual applications of face verifications or identification such as security.

Various facial images of the same people may be changed due to alterations in photometric and geometric parameters. Geometric characteristics denote the geometry of the camera with respect to the face being captured containing distance and orientation and pose. Photometric parameters notify the illumination conditions such as number, size, intensity, placement, and color of light sources. It is clear that varying lighting conditions can create too dark or too light images, which can produce some problems in recognition or verification process or reduce the performance of them.

Researchers have suggested several techniques to create illumination invariant face images. These methods can be divided into 3 categories. In the first category, which is named preprocessing approach, the illumination is compensated by applying pre-processing methods on the pixel values utilizing information from the local area around that pixel. "Local Binary Patterns" (Heusch et al., 2006), "Histogram Equalization"(Shan et al., 2003) , and "Wavelet Transform" (Du and Ward, 2005) are three samples of this method. The simplicity and being in a direct manner are two properties of these methods. These approaches are unable to model the global illumination conditions. In invariant feature extraction methods, investigators try to extract facial features, which are changeless to illumination. Edge map and Gabor-like filters are two examples of this approach". (Adini et al., 1997). Third category is named physical face modeling. In this category, investigators appraise a global physical model of the illumination mechanism and its interaction with the facial surface . "Quotient Image"(Shashua and Riklin-Raviv,

2001), "Spherical Harmonics" (Basri and Jacobs, 2003), "3D morphable" (Banz and Vetter, 1999), and "Discrete Cosine Transform" (Chen et al., 2006) are examples of this category.

Nowadays, because of the effect of changing in the illumination conditions, which makes strong variations in the appearance of a face, illumination invariant face verification is described by various approaches (Zhao et al., 2003). To be more particular, the altering energy and direction distribution of the ambient illumination, together with the 3D structure of the human face, can cause major variations in the shading and shadows on the face. Such changes in the face appearance due to variation illumination can be much larger than the change due to personal identity.

Most of the existing approaches attempt to normalize diffuse reflection in illumination variation. There are still many challenges in specular reflection, attached shadow and cast shadow. Diffuse reflection happens when the object scatters the incident. When the object clearly reflects incident light, specular reflection will appear. In the attached shadow, the object blocks the incident light. When the incident light is hindered by a different object, cast shadow appears (Nishiyama et al., 2008). Figure 1.1 shows various classification of facial appearance caused by illumination (Nishiyama et al., 2008).

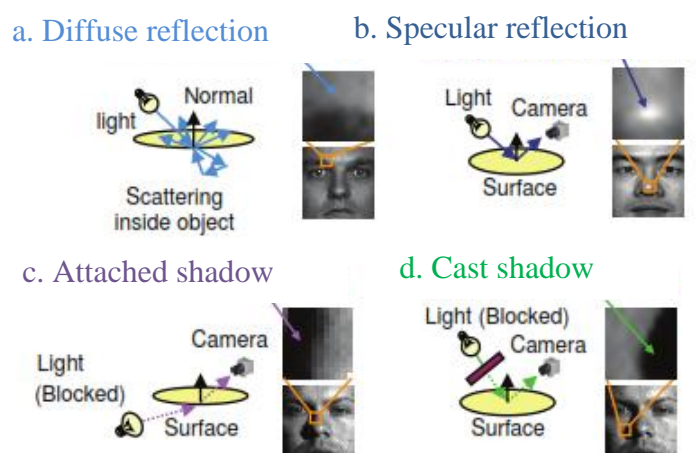


Figure 1.1 Classifying of facial appearance (Nishiyama et al., 2008). (a) "Diffuse reflection"; (b) "Specular reflection"; (c) "Attached shadow"; (d) "Cast shadow"

This research aims to provide a fusion approach to combine three illumination normalization methods together for increasing accuracy and performance of human face verification under illumination variations, including "diffuse reflections", "specular reflections", "attached shadow" and "cast shadows". Because of using three effective illumination normalization techniques and compensating all four mentioned problems produced by illumination, fusion of these methods is very impressive to improve accuracy and performance of face verification under illumination variation. The method of fusion is compared against existing methods of using single normalization techniques for face verifications under varying illuminations.

1.3 Objectives of the Study

1. To investigate state of the art in Illumination normalization approaches.
2. To develop a fusion illumination normalization method for face verification under illumination variations.
3. To evaluate the proposed technique with other current methods with respect to the related performance criteria.

1.4 Scope of the Study

In this study, only lighting variation is considered and other problems in human face verification are not regarded. The face images considered are in frontal position.

For implementation of face verification under illumination variations, three processes were considered as important, which are: preprocessing normalization, physical face modeling, and photometric Normalization.

In this research, several preprocessing normalization methods such as Histogram Equalization (HE) (Shan et al., 2003) , Local Binary Patterns (LBP) (Adini et al., 1997; Heusch et al., 2006), and Discrete Wavelet Transforms (DWT) (Goh et al., 2009) were surveyed, and Spherical Harmonics (SH) (Adini et al., 1997),and Discrete Cosine Transform (DCT) (Chen et al., 2006), Quotient Image (QI) (Shashua and Riklin-Raviv, 2001), and "3D morphable" (Blanz and Vetter, 1999) as physical face modeling methods were studied, and Homomorphic Filtering (HF) (Delac et al., 2006) ,and "Classified Appearance-based Quotient Image" (CAQI) (Nishiyama and Yamaguchi, 2006) as photometric normalization approaches were investigated. Finally, DCT, DWT, and CAQI were used to normalization process.

Un-trained fusion methods such as Max-Rule, Min-Rule, and Ave-Rule were used in order to get a unified decision with a reduced error rate.

The experiments were done on XM2VTS and Yale database B.

1.5 Summary

Over the last three decades, biometrics has been applied as an automated technique to identify individuals according to their behavioral or physical parameters. A biometric system is a pattern identification system. Various biometric properties such as DNA, sample of voice, and face are used in different systems. Face recognition and verification are categorized as natural uncomplicated biometric techniques. In face verification, the investigators determine whether an identity claim is true or false. In face recognition, in order to specify the identity of the query face, researchers compare a probe image against all template images in a database.

In spite of numerous usages of face identification and the availability of feasible approaches after thirty-five years of research, several challenges such as occlusion, varying to pose, illumination variation, expression remain unsolved that researchers should address. One of the critical factors, which effects on face

identification and its performance is illumination variation. In this problem, similar face appears variously due to vary lighting condition.

Nowadays, several approaches exist to overcome the illumination problem. Most of the existing approaches attempt to normalize "diffuse reflection" in illumination variation. There are still many challenges in "specular reflection", "attached shadow" and "cast shadow". This research attempts to supply fusion approach to combine three illumination normalization methods together for increasing performance in normalization of illumination variation.

As mentioned in scope of the study, DWT and DCT and CAQI techniques were chosen to combine in order to cope with illumination variation in face verification. Moreover, XM2VTS and Yale database B were used for the experiment.

In this study, in order to obtain better performance in face verification under illumination variation, un-trained fusion techniques that are Min-Rule, Max-rule, and Ave-rule were applied.

REFERENCES

- Abbas, A., Khalil, M., AbdelHay, S. and Fahmy, H. M. (2009). Illumination invariant face recognition in logarithm discrete cosine transform domain. *Proceedings of the 16th IEEE International Conference on Image Processing (ICIP), 2009* Eng. Dept., Ain Shams University., Cairo, Egypt pp. 4157-4160.
- Abdi, H. and Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*. University of Toronto Scarborough, Ontario, Canada. 2(4), pp. 433-459.
- Adini, Y., Moses, Y. and Ullman, S. (1997). Face recognition: The problem of compensating for changes in illumination direction. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 19(7), pp. 721-732.
- Arandjelovic, O. and Cipolla, R. (2006). A new look at filtering techniques for illumination invariance in automatic face recognition. *Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition, FGR 2006*. . Dept. of Eng., Cambridge University. UK., pp. 449-454.
- Baron, R. J. (1981). Mechanisms of human facial recognition. *International Journal of Man-Machine Studies*. 15(2), pp. 137-178.
- Basri, R. and Jacobs, D. W. (2003). Lambertian reflectance and linear subspaces. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, . 25(2), pp. 218-233.
- Batur, A. U. and Hayes, M. (2001). Linear subspaces for illumination robust face recognition. *Proceedings of the IEEE Computer Society on Vision and Pattern Recognition, CVPR 2001*. Atlanta, GA, USA pp. II-296-II-301 vol. 292.
- Belhumeur, P. N., Hespanha, J. P. and Kriegman, D. J. (1997). Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 19(7), pp. 711-720.

- Beymer, D. and Poggio, T. (1995). Face recognition from one example view. *Proceedings of the Fifth International Conference on Computer Vision, 1995*. Artificial Intelligence Lab., MIT, Cambridge, MA, USA, pp. 500-507.
- Bischof, H., Wildenauer, H. and Leonardis, A. (2001). Illumination insensitive eigenspaces. *Proceedings of the Eighth IEEE International Conference on Computer Vision, 2001. ICCV 2001*. . Vienna University. of Technol., Austria pp. 233-238.
- Blanz, V. and Vetter, T. (1999). A morphable model for the synthesis of 3D faces. *Proceedings of the 26th annual conference on Computer graphics and interactive techniques*. New York ,USA, pp. 187-194.
- Blanz, V. and Vetter, T. (2003). Face recognition based on fitting a 3D morphable model. *Proceedings of the IEEE Transactions on Pattern Analysis and Machine Intelligence*. Saarbrucken, Germany, pp. 1063-1074.
- Brunelli, R. and Poggio, T. (1993). Face recognition: Features versus templates. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 15(10), pp. 1042-1052.
- Chellappa, R., Wilson, C. L. and Sirohey, S. (1995). Human and machine recognition of faces: A survey. *Proceedings of the IEEE*. 83(5), pp. 705-741.
- Chen, C.-P. and Chen, C.-S. (2005). Lighting normalization with generic intrinsic illumination subspace for face recognition. *Proceedings of the Tenth IEEE International Conference on Computer Vision (ICCV'05)*. Sinica, Taipei, pp. 1089-1096.
- Chen, W., Er, M. J. and Wu, S. (2006). Illumination compensation and normalization for robust face recognition using discrete cosine transform in logarithm domain. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*. 36(2), pp. 458-466.
- Delac, K., Grgic, M. and Kos, T. (2006). Sub-image homomorphic filtering technique for improving facial identification under difficult illumination conditions. *Proceedings of the International Conference on Systems, Signals and Image Processing Budapest*. Department of Wireless Communications Unska 3 / XII, HR-10000 Zagreb, Croatia, pp. 95-98.

- Du, S. and Ward, R. (2005). Wavelet-based illumination normalization for face recognition. *Proceedings of the IEEE International Conference on Image Processing, 2005. ICIP 2005*. Vancouver, BC, Canada pp. II-954-957.
- Duan, J., Zhou, C.-G., Liu, X.-H., Zhang, L.-B. and Liu, M. (2004). The methods of improving variable illumination for face recognition. *Proceedings of the International Conference on Machine Learning and Cybernetics*. Changchun, China, pp. 3918-3923.
- Emadi, M., Navabifar, F., Khalid, M. and Yusof, R. (2011). A Review of Methods for Face Verification under Illumination Variation. *Proceedings of the International conference on Image processing (WorldComp2011)* Las Vegas, USA, pp. 171-181.
- Freund, Y., Schapire, R. and Abe, N. (1999). A short introduction to boosting. *Journal-Japanese Society For Artificial Intelligence*. 14(771-780), p. 1612.
- Gao, Y. and Leung, M. K. H. (2002). Face recognition using line edge map. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 24(6), pp. 764-779.
- Georghiades, A. S., Belhumeur, P. N. and Kriegman, D. J. (2000). From few to many: Generative models for recognition under variable pose and illumination. *Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition, 2000*. Yale University., New Haven, CT, USA. , pp. 277-284.
- Georghiades, A. S., Belhumeur, P. N. and Kriegman, D. J. (2001). From few to many: Illumination cone models for face recognition under variable lighting and pose. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 23(6), pp. 643-660.
- Goh, Y. Z., Teoh, A. B. J. and Goh, K. O. M. (2009). Wavelet-based illumination invariant preprocessing in face recognition. *Journal of Electronic Imaging*. 18, p. 023001.
- Goldstein, A. J., Harmon, L. D. and Lesk, A. B. (1971). Identification of human faces. *Proceedings of the IEEE*. 59(5), pp. 748-760.
- Gonzalez, R. C. and Woods, R. E. (2002). *Digital image processing*.
. Dehli, India: Prentice-Hall.

- Gross, R. and Brajovic, V. (2003). An image preprocessing algorithm for illumination invariant face recognition. *Audio-and Video-Based Biometric Person Authentication*. 2688(2003), pp. 1055-1055.
- Grudin, M. A. (1997). *A compact multi-level model for the recognition of facial images*. PhD thesis, Liverpool John Moores University, Liverpool,UK.
- Guo, G., Li, S. Z. and Chan, K. (2000). Face recognition by support vector machines. *Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition, 2000*. Nanyang Technol. University., Singapore pp. 196-201.
- Hallinan, P. W. (1994). A low-dimensional representation of human faces for arbitrary lighting conditions. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition CVPR'94.*, . Harvard University., Cambridge, MA, USA, pp. 995-999.
- Heisele, B., Ho, P. and Poggio, T. (2001). Face recognition with support vector machines: Global versus component-based approach. *Proceedings of the Eighth IEEE International Conference on Computer Vision, ICCV 2001*. MIT, USA, pp. 688-694.
- Heisele, B. and Koshizen, T. (2004). Components for face recognition. *Proceedings of the Sixth IEEE International Conference on Automatic Face and Gesture Recognition*. Boston, MA, USA, pp. 153-158.
- Heusch, G., Rodriguez, Y. and Marcel, S. (2006). Local binary patterns as an image preprocessing for face authentication. *Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition, 2006. FGR 2006.* . Ecole Polytech Federale de Lausanne, Martigny, pp. 6 pp.-14.
- Horn, B. K. P. (1986). *Robot vision*. USA: MIT press.
- Huang, R., Pavlovic, V. and Metaxas, D. N. (2004). A hybrid face recognition method using markov random fields. *Proceedings of the Pattern Recognition, 2004. ICPR 2004*. Rutgers University., USA. , pp. 157-160.
- Jobson, D. J., Rahman, Z. and Woodell, G. A. (1997). A multiscale retinex for bridging the gap between color images and the human observation of scenes. *IEEE Transactions on Image Processing*. 6(7), pp. 965-976.

- Johnson, A. E. and Hebert, M. (1999). Using spin images for efficient object recognition in cluttered 3D scenes. *IEEE Transactions on Image Processing*. 21(5), pp. 433-449.
- Jonsson, K., Kittler, J., Li, Y. and Matas, J. (2002). Support vector machines for face authentication. *Image and Vision Computing*. 20(5-6), pp. 369-375.
- Joshi, M. A. (2006). *Digital image processing: An algorithmic approach*. New Delhi: PHI Learning Pvt. Ltd. Prentice-Hall.
- Kanade, T. (1973). *Picture processing system by computer complex and recognition of human faces*. Kyoto, Japon: Department of Science, Kyoto University.
- Kaya, Y. and Kobayashi, K. (1972). *A basic study on human face recognition*. New York, USA: Academic Press.
- Kee, S. C., Lee, K. M. and Lee, S. U. (2000). Illumination invariant face recognition using photometric stereo. *IEICE TRANSACTIONS ON INFORMATION AND SYSTEMS E SERIES D*. 83(7), pp. 1466-1474.
- Khayam, S. A. (2003). *The discrete cosine transform (DCT): theory and application*. Michigan State University.
- Kim, K. I., Kim, J. H. and Jung, K. (2002). Face recognition using support vector machines with local correlation kernels. *International journal of pattern recognition and artificial intelligence*. 16(1), pp. 97-112.
- Kim, T.-K., Kim, H., Hwang, W., Kee, S.-C. and Kittler, J. (2003). Face description based on decomposition and combining of a facial space with LDA. *Proceedings of the International Conference on Image Processing, ICIP 2003*. Samsung AIT, South Korea. , pp. III-877-880 vol. 872.
- Kim, T. K., Kim, H., Hwang, W. and Kittler, J. (2005). Component-based LDA face description for image retrieval and MPEG-7 standardisation. *Image and Vision Computing*. 23(7), pp. 631-642.
- Kirby, M. and Sirovich, L. (1990). Application of the Karhunen-Loeve procedure for the characterization of human faces. *IEEE Transactions on Pattern Analysis and Machine Intelligence*,. 12(1), pp. 103-108.
- Kittler, J., Li, Y. and Matas, J. (2000). On matching scores for LDA-based face verification. *Proceedings of the British Machine Vision Conference*. University of Surrey, Guildford, Surrey GU2 7XH, UK, pp. 42-51.

- Kumar, B. V. K. V., Mahalanobis, A. and Juday, R. D. (2005). *Correlation pattern recognition*. New York,USA: Cambridge University Press.
- Lades, M., Vorbruggen, J. C., Buhmann, J., Lange, J., von der Malsburg, C., Wurtz, R. P. and Konen, W. (1993). Distortion invariant object recognition in the dynamic link architecture. *IEEE Transactions on Computers*. 42(3), pp. 300-311.
- Land, E. H. and McCann, J. J. (1971). Lightness and retinex theory. *Journal of the Optical society of America*. 61(1), pp. 1-11.
- Lawrence, S., Giles, C. L., Tsoi, A. C. and Back, A. D. (1997). Face recognition: A convolutional neural-network approach. *IEEE Transactions on Neural Networks*,. 8(1), pp. 98-113.
- Leonardis, A. and Bischof, H. (2000). Robust recognition using eigenimages. *Computer Vision and Image Understanding*. 78(1), pp. 99-118.
- Li, S. Z. and Jain, A. K. (2011). *Handbook of face recognition*. Michigan state University,USA: Springer.
- Li, Y. (2000). *Linear Discriminant Analysis and its application to face Identification*. University of Surrey, Surrey, UK.
- Lin, C. J. (2001). On the convergence of the decomposition method for support vector machines. *IEEE Transactions on Neural Networks*. 12(6), pp. 1288-1298.
- Liu, C. and Wechsler, H. (2002). Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. *IEEE Transactions on Image Processing*. 11(4), pp. 467-476.
- Liu, D. H., Lam, K. M. and Shen, L. S. (2005). Illumination invariant face recognition. *Pattern Recognition*. 38(10), pp. 1705-1716.
- Mallat, S. (1999). *A wavelet tour of signal processing*. California,USA: Academic press,Elsiver.
- Manjunath, B., Chellappa, R. and von der Malsburg, C. (1992). A feature based approach to face recognition. *Proceedings of the Computer Vision and Pattern Recognition, 1992. CVPR'92*. California University., Santa Barbara, CA, USA, pp. 373-378.
- Martinez, A. M. (1998). The AR face database. *CVC Technical Report*. 24(1998).
- Méndez-Vázquez, H., Kittler, J., Chan, C. H. and García-Reyes, E. (2010). On combining local DCT with preprocessing sequence for face recognition under

- varying lighting conditions. *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications*. 6419(2010), pp. 410-417.
- Messer, K., Matas, J., Kittler, J., Luetttin, J. and Maitre, G. (1999). XM2VTSDB: The extended M2VTS database. *Proceedings of the Second international conference on audio and video-based biometric person authentication*. Washington D.C, USA, pp. 965-966.
- Moghaddam, B., Pentland, A., Vision, M. I. o. T. M. L. and Group, M. (1994). *Face recognition using view-based and modular eigenspaces*. MA,USA: Vision and Modeling Group, Media Laboratory, Massachusetts Institute of Technology.
- Mukaigawa, Y., Ishii, Y. and Shakunaga, T. (2006). Classification of photometric factors based on photometric linearization. *Computer Vision-ACCV 2006*. 3852 (2006), pp. 613-622.
- Mukaigawa, Y., Ishii, Y. and Shakunaga, T. (2007). Analysis of photometric factors based on photometric linearization. *JOSA A*. 24(10), pp. 3326-3334.
- Mukaigawa, Y., Miyaki, H., Mihashi, S. and Shakunaga, T. (2001). Photometric image-based rendering for image generation in arbitrary illumination. *Proceedings of the Eighth IEEE International Conference on Computer Vision, ICCV 2001*. Okayama University., Japan, pp. 652-659.
- Nayar, S. K. and Bolle, R. M. (1996). Reflectance based object recognition. *International Journal of Computer Vision*. 17(3), pp. 219-240.
- Nishiyama, M., Kozakaya, T. and Yamaguchi, O. (2008). Illumination Normalization using Quotient Image-based Techniques. *Recent Advances in Face Recognition, I-Tech, Vienna, Austria*. pp. 97-108.
- Nishiyama, M. and Yamaguchi, O. (2006). Face recognition using the classified appearance-based quotient image. *Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition, 2006. FGR 2006*. Toshiba Corp., Tokyo, Japan, pp. 6 pp.-54.
- Okabe, T. and Sato, Y. (2003). Object recognition based on photometric alignment using RANSAC. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*., University of Tokyo, Japan, pp. I-221-I-228 vol. 221.

- Pang, S., Kim, D. and Bang, S. Y. (2003). Membership authentication in the dynamic group by face classification using SVM ensemble. *Pattern Recognition Letters*. 24(1), pp. 215-225.
- Pennebaker, W. B. and Mitchell, J. L. (1993). *JPEG still image data compression standard*. Massachusetts, USA: Kuwer Academic publisher.
- Pentland, A., Moghaddam, B. and Starner, T. (1994). View-based and modular eigenspaces for face recognition. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition CVPR'94.*, MIT, MA, USA, pp. 84-91.
- Petrou, M. and Petrou, C. (2010). *Image processing: the fundamentals*. Chennai, India: Laserwords private Ltd.
- Pizer, S. M., Amburn, E. P., Austin, J. D., Cromartie, R., Geselowitz, A., Greer, T., ter Haar Romeny, B., Zimmerman, J. B. and Zuiderveld, K. (1987). Adaptive histogram equalization and its variations. *Computer vision, graphics, and image processing*. 39(3), pp. 355-368.
- Ramamoorthi, R. and Hanrahan, P. (2001). On the relationship between radiance and irradiance: determining the illumination from images of a convex Lambertian object. *JOSA A*. 18(10), pp. 2448-2459.
- Sadeghi, M. and Kittler, J. (2006). Confidence based gating of multiple face authentication experts. *Structural, Syntactic, and Statistical Pattern Recognition*. 4109(2006), pp. 667-676.
- Samaria, F., Fallside, F. and Ltd, O. R. (1993). *Face identification and feature extraction using hidden markov models*. Cambridge, UK: Citeseer.
- Samaria, F. S. and Harter, A. (1994). Parameterisation of a stochastic model for human face identification. *Proceedings of the IEEE Workshop on Applications of Computer Vision*. Cambridge University., UK, pp. 138-142.
- Shan, S., Gao, W., Cao, B. and Zhao, D. (2003). Illumination normalization for robust face recognition against varying lighting conditions. *Proceedings of the IEEE International Workshop on Analysis and Modeling of Faces and Gestures, 2003*. Inst. of Comput. Technol., Beijing, China, pp. 157-164.
- Shashua, A. (1992). *Geometry and photometry in 3D visual recognition*. PhD Thesis, Massachusetts Institute of Technology, Massachusetts, USA.

- Shashua, A. (1997). On photometric issues in 3D visual recognition from a single 2D image. *International Journal of Computer Vision*. 21(1), pp. 99-122.
- Shashua, A. and Riklin-Raviv, T. (2001). The quotient image: Class-based re-rendering and recognition with varying illuminations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*,. 23(2), pp. 129-139.
- Short, J. (2006). *Illumination Invariance for Face Verification*. PhD thesis, Centre for Vision, Speech and Signal Processing School of Electronics and Physical Sciences, University of Surrey Guildford, Surrey UK, surrey.
- Sim, T., Baker, S. and Bsat, M. (2002). The CMU pose, illumination, and expression (PIE) database. *Proceedings of Robotics Inst.*, Carnegie Mellon University., Pittsburgh, PA, USA. , pp. 46-51.
- Sirovich, L. and Kirby, M. (1987). Low-dimensional procedure for the characterization of human faces. *JOSA A*. 4(3), pp. 519-524.
- Stonham, T. (1986). Practical face recognition and verification with WISARD. *Aspects of Face Processing, Martinus Nijhoff Publishers, Dordrecht*.
- Strang, G. (1999). The discrete cosine transform. *SIAM review*. pp. 135-147.
- Štruc, V., Žibert, J. and Pavešić, N. (2009). Histogram remapping as a preprocessing step for robust face recognition. *image*. 7(8), p. 9.
- Takacs, B. (1998). Comparing face images using the modified Hausdorff distance. *Pattern Recognition*. 31(12), pp. 1873-1881.
- Tan, X. and Triggs, B. (2010). Enhanced local texture feature sets for face recognition under difficult lighting conditions. *IEEE Transactions on Image Processing*. 19(6), pp. 1635-1650.
- Tang, H.-M., Lyu, M. R. and King, I. (2003). Face recognition committee machine. *Proceedings of the Proceedings.(ICASSP'03). 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing*,. pp. II-837-840 vol. 832.
- Tolba, A., El-Baz, A. and El-Harby, A. (2005). Face recognition: A literature review. *International Journal of Signal Processing*. 2(2), pp. 88-103.
- Turk, M. and Pentland, A. (1991). Eigenfaces for recognition. *Journal of cognitive neuroscience*. 3(1), pp. 71-86.
- Vapnik, V. N. (2000). *The nature of statistical learning theory*. New York, USA: Springer-Verlag New York Inc.

- Vetter, T. and Blanz, V. (1998). Estimating coloured 3D face models from single images: An example based approach. *Computer Vision—ECCV'98*. 1407(1998), pp. 499-513.
- Vetter, T., Jones, M. J. and Poggio, T. (1997). A bootstrapping algorithm for learning linear models of object classes. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1997*. Kybernetik, Tübingen, Germany, pp. 40-46.
- Vishwakarma, V. P., Pandey, S. and Gupta, M. (2007). A novel approach for face recognition using DCT coefficients re-scaling for illumination normalization. *Proceedings of the International Conference on Advanced Computing and Communications. ADCOM 2007* Guru Gobind Singh Indraprastha University., Delhi pp. 535-539.
- Wang, H., Li, S. Z. and Wang, Y. (2004). Generalized quotient image. *Proceedings of the Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2004*. Inst. of Autom., Chinese Acad. of Sci., Beijing, China pp. II-498-II-505 Vol. 492.
- Woodham, R. J. (1980). A photometric method for determining surface orientation. *Optical engineering*. 1(7), pp. 139-144.
- Xie, X. and Lam, K. M. (2005). Face recognition under varying illumination based on a 2D face shape model. *Pattern Recognition*. 38(2), pp. 221-230.
- Zhang, D., Jing, X. Y. and Yang, J. (2006). Linear discriminant analysis. *Biometric Image Discrimination Technologies: Computational Intelligence and Its Applications Series, IGI Global, Hershey, Pennsylvania, USA*. pp. 41-64.
- Zhang, L., Li, S. Z., Qu, Z. Y. and Huang, X. (2004). Boosting local feature based classifiers for face recognition. *Proceedings of the Conference on Computer Vision and Pattern Recognition Workshop, CVPRW'04* Lanzhou University, Lanzhou, China, pp. 87-89.
- Zhang, L. and Samaras, D. (2006). Face recognition from a single training image under arbitrary unknown lighting using spherical harmonics. *Pattern Analysis and Machine Intelligence*, . 28(3), pp. 351-363.
- Zhao, L. and Yang, Y. H. (1999). Theoretical analysis of illumination in PCA-based vision systems. *Pattern Recognition*. 32(4), pp. 547-564.

- Zhao, W., Chellappa, R., Phillips, P. J. and Rosenfeld, A. (2003). Face recognition: A literature survey. *Acm Computing Surveys (CSUR)*. 35(4), pp. 399-458.
- Zhao, W. Y. and Chellappa, R. (2000). SFS based view synthesis for robust face recognition. *Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition, 2000*. Center for Autom. Res., Maryland Univesity., College Park, MD, USA, pp. 285-292.
- Zou, X., Kittler, J. and Messer, K. (2007). Illumination invariant face recognition: A survey. *Proceedings of the First IEEE International Conference on Biometrics: Theory, Applications, and Systems, BTAS 2007*. Surrey University., Guildford pp. 1-8.