



A novel method for efficient face recognition based on illumination invariant elastic bunch graph matching

¹S.Venkatesan, ²Srinivasa Rao Madane

¹Dept. of Computer Science & Engg, Anna University of Technology, Coimbatore,

²Dept. of Computer Science & Engg, Priyadarshini College of Engineering, Vaniyambadi.

ARTICLE INFO

Article history:

Received: 16 February 2011;

Received in revised form:

16 March 2011;

Accepted: 25 March 2011;

Keywords

Facial expression and emotions,
Occlusion,
Image orientation,
Pose.

ABSTRACT

Making recognition more reliable under uncontrolled lighting conditions is one of the most important challenges for practical face recognition systems. This paper proposes a system which can handle illumination problem of face recognition systems by using “Retinex and color constancy” algorithm. The Retinex and color constancy approach has been plugged with Elastic Bunch Graph Matching (EBGM). The proposed system has been tested on FERET database having more than 1000 face images. The experimental results demonstrate that performance of the proposed system is superior to the known systems with the increase in accuracy.

© 2011 Elixir All rights reserved.

Introduction

During the past decade, face recognition has drawn significant attention [1][2][3][4] from the perspective of different applications. A general statement of the face recognition problem can be formulated as follows. Given still or video images of a scene, the problem is to identify or verify one or more persons in the scene using a stored database of faces. The environment surrounding a face recognition application can cover a wide spectrum – from a well controlled environment to an uncontrolled one. In a controlled environment, frontal and profile photographs of human faces are taken complete with a uniform background and identical poses among the participants. In the case of uncontrolled environment, recognition of human faces is to be done at different scales, positions, luminance and orientations; facial hair, makeup and turbans etc.

This challenging and interesting problem has attracted researchers from various background i.e., psychology, pattern recognition, neural networks, computer vision and computer graphics. The challenges associated with face recognition can be attributed to the following factors:

Pose: The images of a face vary due to the relative camera-face pose (frontal, tilted, profile, upside down).

Presence or absence of structural components: Facial features such as beards, mustaches, and glasses may or may not be present and there is a great deal of variability among these components including shape, color and size.

Facial expression and emotions: The appearance of faces is directly affected by a person’s facial expression and emotions.

Occlusion: Faces may be partially occluded by other objects. For an example, in an image with a group of people, some faces may partially occlude other faces.

Image orientation: Face images directly vary for different rotations about the camera’s optical axis.

Imaging conditions: When the image is formed, factors such as lighting and camera characteristics affect the appearance of a face.

In general, face recognition algorithms can be divided into two groups based on the face representation. They are:

1. Appearance-based which uses holistic texture features and is applied to either whole-face or specific regions in a face image.
2. Feature-based which uses geometric facial features (mouth, eyes, brows, cheeks etc.) and geometric relationships between them.

Holistic based method uses the whole face region as input to the recognition system. Subspace analysis is done by projecting an image into a lower dimensional subspace formed with the help of training face images and after that recognition is performed by measuring the distance between known images and the image to be recognized. The most challenging part of such a system is finding an adequate subspace. Some well known face recognition algorithms for face recognition are Principal Component Analysis (PCA) [5][6], Independent Component Analysis (ICA) [7], Linear Discriminant Analysis (LDA) [8] and Probabilistic neural network Analysis (PNNA) [9]. However all the holistic based algorithms are very much dependent on the design decisions which involve the method of subspace analysis, varying the dimension of the subspace and choosing the similarity measure. Apart from this the successful implementation of these algorithms involves huge training set with multiple images in different pose and expression for each person. The performance of these algorithms varies under different training set. The choice of best design is still unsolved. On the other hand, feature based methods extract local features like eyes, nose, and mouth and they are fed into the structural classifier. The example includes Elastic Bunch Graph Matching (EBGM) [10]. The major advantage of EBGM is instead of performing holistic approaches it recognizes the faces by comparing their parts. The algorithm is memory efficient as the face is represented in internal form as face graph containing node for each landmark position with the corresponding extracted features. Hence it needs less human efforts. Also the

system does not require large training set for efficient recognition.

One of the major disadvantages of the system is that eyes should be open as the system aligns the images on the basis of eyes locations. Another limitation of the system is that the system is not illumination invariant. The change in lightning conditions deteriorates the results of a system. Considering the advantages of the EBGm algorithm over other existing holistic and feature based face algorithms, this algorithm has been used for employing illumination invariance. The idea is to preprocess the input image with illumination invariance algorithm to remove the effect of change in luminance which is then passed to EBGm algorithm for recognition.

Retinex method is a powerful image enhancement tool first introduced by Edwin Land forty years ago [11]. It is used for wide range of applications like dynamic range compression, gamut mapping and illumination invariance. The Retinex Algorithm together with color constancy handles the problem of separating the illumination from reflectance thereby compensating for non-uniform lightning.

This paper makes use of this idea given in Retinex to handle illumination/lightning problems in EBGm proposing an illumination invariant face recognition system. Next Section provides the detailed discussion on the proposed system. Results are presented Section 3. The paper is concluded in Section 4.

The proposed system

The input image is preprocessed by separating the illumination from the reflectance part. Separating the illumination from the source image yields the reflectance image, which is expected to be free of non-uniform illumination. This illumination estimation problem can be formulated as a Quadratic Programming optimization problem that can be efficiently solved by the Projected Normalized Steepest Descent (PNsD) algorithm [12], accelerated by a multi-resolution technique.

The RETINEX algorithm [13] can be used for the enhancement of the different regions of the image. The algorithm has been used twice.

At first the algorithm is applied on the input image in order to enhance details in dark areas of the image. The algorithm is invoked again on the inverse image (the result is re-inverted afterwards) to enhance details in bright areas of the image. Both the RETINEX images together reveal more details as compared to the input image.

After applying the Retinex algorithm, the image is further enhanced by histogram equalization, color restoration and image stretching. This illumination invariant image is passed to the EBGm algorithm for recognition purpose.

Retinex Algorithm

RETINEX algorithm [13] decomposes a given image S into two images: the reflectance image R , and the illumination image L , such that each point in the image domain $S(x, y)$ can be expressed as Equation 1,

$$S(x, y) = R(x, y) \cdot L(x, y) \quad (1)$$

By taking the image to the logarithmic domain, one get $s = l + r$ where $s = \log S$, $l = \log L$ and $r = \log R$. The algorithm assumes spatial smoothness of the illumination field. In addition, knowledge of the limited dynamic range of the reflectance is used as a constraint in the recovery process.

The physical nature of reflecting objects is such that they reflect only a part of the incident light. Thus, the reflectance is restricted to the range $R \in [0, 1]$, and $L \geq S$, which implies $l \geq s$. Thus the retinex algorithm is used to reduce the image into reflectance and illumination image [11][13]. The two iterations of the algorithms are applied on the original and inverted image to give bright and dark retinex which reveal more information from the original image as shown in Figure 1(a) and Figure 1(b)



Figure1 (a) Bright Retinex



Figure 1 (b) Dark Retinex

The reflectance image obtained by the RETINEX is sometimes an over-enhanced image. This may be due to the facts that 1) the human visual system usually prefers some illumination in the image and that 2) removal of complete illumination exposes the image to noise that might exist in darker regions of the original image.

The illumination image, $L = \exp(l)$, is tuned by a Gamma correction with a free parameter γ to obtain a new illumination image L' and multiply it by R , which gives the output image $S' = L' \cdot R$. The Gamma Correction is given by Equation 2.

$$L' = W \cdot [L / W]^{1/\gamma} \quad (2)$$

where W is the highest value of dynamic range (equal to 255 in 8-bit images). Multiplying L' by R one gets the image S' as given in Equation 3

$$S' = L' \cdot R = (L'/L) \cdot S \quad (3)$$

Note for $\gamma=1$, $S'=S$ i.e., the whole illumination is added back and for $\gamma=\infty$, $S' = R \cdot W$ i.e., no illumination is added back which is the same reflectance image, R , as obtained by the original RETINEX, stretched to the interval $[0, W]$.

The RETINEX algorithm is applied over the input image and its inverse, to produce bright and dark RETINEX images. After Gamma correction these two images are combined together by using the average operation between bright and dark RETINEX images as shown in Figure 2.



Figure 2: Combined image

Histogram enhancement

The RETINEX algorithm reveals details in the bright and dark areas, but it shifts the colors once again towards the middle of the spectrum thus giving non-uniform histogram. Thus to get more uniform distribution without losing colors histogram enhancement is done.

Color restoration

To restore color loss, each channel's i.e., Red, Green and Blue, relative color is calculated from the original image and then, each pixel of the enhanced image is multiplied by its relative color as given in Equation 4:

$$R'_{channel} = R_{channel} \cdot f\left(\frac{I_{channel}}{I_R + I_G + I_B}\right) \quad (4)$$

where f is an ascending monotonic function that may be linear or logarithmic. $I_{channel}$ is the channel of the image i.e., R, G and B . I_R is the value of Red channel, I_G is the value of Green channel and I_B is the value of Blue channel.

But the Color Restoration stage may create colors out of the normal color range. Therefore there is a need to use the Image Stretching stage after Color Restoration.

Image stretching

Even after the Histogram Enhancement stage, usually there is still a few percent of the color-space left unused or rarely used. Although there is no need to care much about few overexposed or underexposed pixels, one may like to increase the image visual range by stretching the image [14], by saturating a small percentage of the image. The idea is to map the pixel range into new range i.e., [0.0, 1.0]. The appropriate linear transformation is used, following by saturating the pixels with colors out of the range. The outcome is the color restored image as it is passed to the EBGM module for verification purpose.

Elastic Bunch Graph Matching (EBGM): Face recognition using elastic bunch graph matching [10] is based on recognizing novel faces by estimating a set of novel features using a data structure called a bunch graph. The algorithm operates in two modes a) Training mode b) Testing mode.

Training mode involves creation of bunch graph by manually selecting the landmarks on training face images to form the model imaginary. These landmarks are convolved with Gabor Wavelet to form Gabor jets. A data structure called bunch graph is created corresponding to facial landmarks that contains a bunch of model jets extracted from the model imaginary. To add every image to the database, the following steps are performed.

Step 1: Estimate and locate Landmark positions with the use of bunch graph as given in Equation 5

$$\vec{p}_n \approx \vec{p}_m + \vec{v}_{mn} \quad (5)$$

where \vec{v}_{mn} is the difference between two nodes of the landmark in bunch graph and \vec{p}_n and \vec{p}_m are average locations of the nodes for two landmarks

Step 2: Calculate the novel jets displacement from the actual position by comparing it to the most similar model jet.

Step 3: Create another data structure namely face graph containing node for each landmark position and jet values for that landmark position.

Similarly for each query image, the landmarks are estimated and located using bunch graph. Then the features are extracted by convolution with the number of instances of Gabor filters followed by the creation of face graph.

The matching score is calculated on the basis of similarity between face graphs of database and query image. Computation of the similarity between landmark jets in face graphs of database and query image is obtained by Equation 6

$$L_{jet}(G, G') = \frac{1}{n} \sum_{i=0}^n S_x(J_i, J'_i) \quad (6)$$

where n is the number of instances of Gabor filter convolved with the landmark point and S_x is a similarity function which can be phase, magnitude etc., J_i, J'_i are the jets extracted from landmark positions and G and G' are face graphs of database and query face image respectively.

The face graph similarity between database and query image is calculated as an average of landmarks jet similarity.

Experimental results

The proposed system has been tested on FERET database consisting of more than 1000 facial images with five images per person in different illumination and expressions. In the first experiment, EBGM algorithm was tested as standalone under different background and lightning conditions. The face images are acquired in light and dark background under different illumination. The images are acquired using SONY digital camera at a distance of about 12 cm. These images are acquired in different sessions. However to maintain the consistency, the same setup is used for image acquisition. The test results have been computed along with FAR, FRR and accuracy Graphs. Table 1 shows the, FAR, FRR and accuracy of the system.

Table 1: FAR, FRR and Accuracy Table

	FAR	FRR	Accuracy
EBGM	2.83%	10.52%	93.32%

In next experiment, RETINEX algorithm has been plugged in together with color constancy method with the EBGM. Retinex and color constancy algorithm is used to preprocess the image to make the image illumination invariant. Testing is performed for the calculation of FAR, FRR and accuracy and the results are found to be very encouraging as shown in Table 2. The FAR and FRR graph is shown in Figure 3 while the accuracy graph is given in Figure 4. The best matching result is shown in Figure 5.

Table 2: FAR, FRR and Accuracy

	FAR	FRR	Accuracy
Proposed System	0.59%	6.49%	96.46%

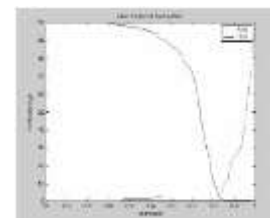


Figure 3: FAR & FRR Graph

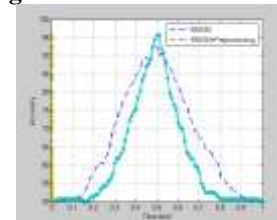


Figure 4: The accuracy Graph



Figure 5: Best Matching Images

Conclusion

We have presented new methods for face recognition under Illumination Invariant Elastic Bunch Graph Matching method.

An efficient face recognition system which can handle the problem of illumination has been proposed. The system first preprocesses the input image and then invokes EBGGM algorithm for recognition. The input image has been preprocessed with Retinex and color constancy which results in invariance to illumination change and performance improvement.

References

1. Y. Adini, Y. Moses, and S. Ullman, "Face recognition: The problem of compensating for changes in illumination direction," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 7, pp. 721–732, Jul. 1997.
2. T. Ahonen, A. Hadid, and M. Pietikainen, "Face recognition with local binary patterns," in *Eur. Conf. Comput. Vis.*, Prague, Czech Republic, 2005, pp. 469–481.
3. T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.
4. R. Basri and D. Jacobs, "Lambertian reflectance and linear subspaces," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 2, pp. 218–233, Feb. 2003.
5. I. T. Jolliffe, *Principal Component Analysis*, 2nd edition. New York, Springer-Verlag, 2002.
6. M. Turk and A. Pentland. *Face Recognition using Eigenfaces*, Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Maui, Hawaii: 586-591, 1991.
7. P. C. Yuen and J. H. Lai. *Independent Component Analysis of Face Images*. IEEE workshop on Biologically Motivated Computer Vision, Seoul, 2000.
8. K. Etemad and R. Chellappa. Discriminant Analysis for recognition of human face images. *Journal of the Optical Society of America A*, 4(8): 1724–1733, 1997
9. S. Haykin. *Neural Networks, A Comprehensive Foundation*, Macmillan, New York, NY, 1994.
10. D. S. Bolme, J. Ross Beveridge, M. L. Teixeira, and B. A. Draper. *The CSU Face Identification Evaluation System: Its Purpose, Features and Structure*. Proceedings 3rd International Conference on Computer Vision Systems, Graz, Austria, 2003.
11. R. Kimmel, D. Shaked and M. Elad. *A Variational Framework for Retinex*.
12. D.P. Bertsekas. *Non-Linear Programming*. Athena Scientific, Belmont, Massachusetts, 1995.
13. Z. Rahmany, D.J. Jobson and G.A. Woodell. *Retinex Processing for Automatic Image Enhancement*. Human Vision and Electronic Imaging VII, SPIE Symposium on Electronic Imaging, SPIE 4662, 2002.
14. Gonzalez, Woods. *Digital Image Processing*. Pearson Education, Second Edition, India, 2002

Authors

Dr.S.Srinivasa Rao Madane Principal and Professor Department of Computer Science & Engineering in Priyadarshini Engineering Vaniyambadi Tamilnadu India. His Area of Interest includes Neural Networks, Image processing, Analog and Digital communication

S.Venkatesan Pursuing Ph.D., in Department of Computer Science and Engineering in Anna University of Technology Coimbatore, Tamilnadu India. His area of interest includes Image Processing, Soft Computing, Pattern Recognition, and Optimization Techniques