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Robust Face Recognition of Variations in Blur and Illumination by Using LDA

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Abstract
Face recognition is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source.In this paper address the problem of unconstrained face recognition from remotely acquired images.The main factors that make this problem challenging are image degradation due to blur,and appearance variations due to illumination and pose.In this paper address the problems of blur and illumination.Here we use a blur and illumination-robust algorithm.Direct Recognition Blurred Face (DRBF)Algorithm for recognizing blurred faces.This algorithm for solving simple convex optimizationproblems.Illumination-Robust Recognition of Blurred Face(IRBF)Algorithm for jointly handling variations due to illumination and blur.This algorithm is used to improve recognition performance and speed.By incorporating Linear Discriminant Analysis in order to obtain a compact and discriminative feature representation where as by using Eigenfaces can obtain only the Eigen feature.

Index Terms: Direct recognition of blurred and illuminated faces, Eigenfaces, Linear Discriminant Analysis(LDA).

I. INTRODUCTION

Face recognition has been an intensely researched field of computer vision for the past couple of decades. One such scenario occurs while recognizing faces acquired from distant cameras. The main factors that make this a challenging problem are image degradations due to blur and noise, and variations in appearance due to illumination and pose.

In this paper,specifically address the problem of recognizing faces across blur and illumination.This approach involves solving the challenging problem of blind image deconvolution.To avoid this unnecessary step and propose a direct approach for face recognition. The set of all images obtained by blurring a given image forms a convex set, and this set is the convex hull of shifted versions of the original image. Thus with each gallery image can associate a corresponding convexset. Based on this set-theoretic characterization, propose a blur-robust face recognition algorithm. In the basic version of our algorithm, compute the distance of a given probe image (which we want to recognize) from each of the convex sets, and assign it the identity of the closest gallery image.The distance-computation steps are formulated as convex optimization problems over the space of blur kernels. however, if this information is available, it can be easily incorporated into our algorithm,resulting in improved recognition performance.

Based on this illumination model, we show that the set of all images of a face under all blur and illumination variations is a biconvex set. If we fix the blur kernel then the set of images obtained by varying the illumination conditions forms a convex set; and if we fix the illumination condition then the set of all blurred images is also convex. Based on this set-theoretic characterization, we propose a blur and illumination robust face recognition algorithm. The basic version of our algorithm computes the distance of a given probe image from each of the bi-convex sets, and assigns it the identity of the closest gallery image.

The rest of the paper is organised as follows: In section II, we introduce Feature extraction in eigen faces Section III presents classification method.

II. FEATURE EXTRACTION

1.Feature Extraction Using Eigen Faces

A training set must contain a list of objects with known classifications. A Training set is a set of images used in training of either a computer system or a human operator. So that it includes both common and rare types of object. creating a training set requires a source of true object classifications. which is usually difficult even for human express to generate if it must rely on the same data being used by the classifier. A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, and pixels. Pixel is the term most widely used to denote the elements of a digital image. Amplitude of fat any pair of coordinates (x,y) is called intensity I or gray value of the image. When spatial coordinates and amplitude values are all finite, discrete quantities, the image is called digital image.

The aim of the face preprocessing step is to normalize the coarse face detection, so that a robust feature extraction can be achieved. Depending of the application, face preprocessing includes: Alignment (translation, rotation, scaling) and light normalization/correlation. Image enhancement of an image involves improvement in its appearance and efficient representation. It means contrast, screening larger or converting one grey level in to another grey level by a predetermined transformation. Image enhancement is among the simplest and most appealing areas of digital image processing. Feature extraction is one of the most widely employed methods for reducing the data dimensionality. The aim of feature extraction is to extract a compact set of interpersonal discriminating geometrical or/and photometrical features of the face.

To understand standard deviation, dataset is needed. The two dataset having the same mean is considered then there exists some problem (how to differ the two datasets). The difference between these two dataset is a measure of how spread the data is. It is the average distance from the mean of the datapoint to a point.Variance measure the spread of data in a dataset.Standard deviation and variance measures are purely one dimensional. However, many datasets have more than one dimensional and aim is to see if there is any relationship between the dimensions. Covariance is one such a measure, i.e. measured between two dimensions. Linear transformations of a vector space, such as rotation, reflection, stretching, compression, shear or any combination of these, may be visualized by the effect they produce on vectors.The normalized training image in the N-dimensional space is stored in a vector of size N. Each of the normalized training face images is mean centered. This is done by subtracting the mean face image from each of the normalized training images.

The mean image is represented as a column vector where each scalar is the mean of all corresponding pixels of the training images,Each of the normalized training face images is mean centered. This is done by subtracting the mean face image from each of the normalized training images. The mean image is represented as a column vector where each scalar is the mean of all corresponding pixels of the training images,Once the training face images are centered, the next process is to create the Eigenspace which is the reduced vectors of the mean normalized training face images. Once the training face images are centered, the next process is to create the Eigenspace which is the reduced vectors of the mean normalized training face images.

A matrix is said to be defective if it fails to have n linearly independent eigenvectors. All defective matrices have fewer than n distinct eigenvalues, but not all matrices with fewer than n distinct eigenvalues are defective.This Fig shows the input image. A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, and pixels. Pixel is the term most widely used to denote the elements of a digital image. Amplitude of fat any pair of coordinates (x,y) is called intensity Ior gray value of the image

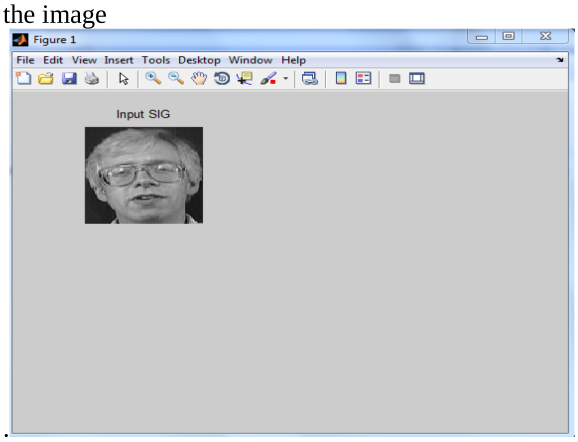

Fig 1.Input image

A Training set is a set of images used in training of either a computer system or a human operator. A training set must contain a list of objects with known classifications. So that it includes both common and rare types of object. creating a training set requires a source of true object classifications. which is usually difficult even for human express to generate if it must rely on the same data being used by the classifier

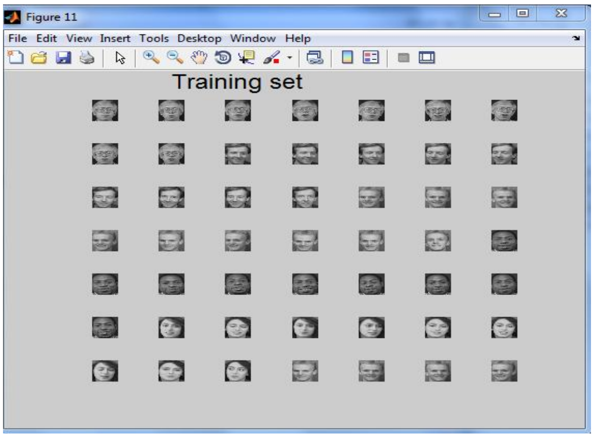

Fig 2 Training Set

The below Fig shows the Normalized Training set Normalization is a process that changes the range of pixel intensity values. Normalization is sometimes called contrast stretching or histogram stretching. Applications include photograph with poor contrast due to glare for example. In more general fields of data processing. Such as digital signal processing it is referred to its dynamic range expansion. Hence the term normalization often the motivation is to achieve consistency in dynamic range for a set of data.

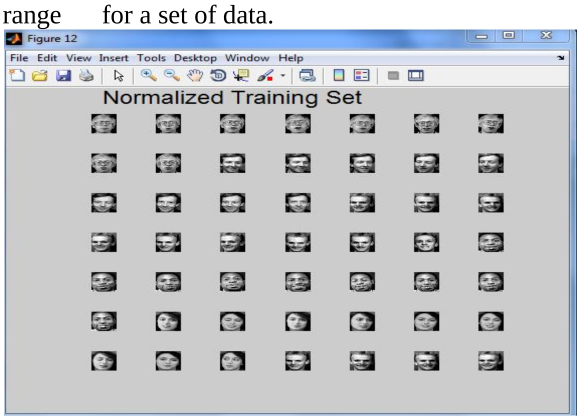

Fig 3 Normalized Training set

The mean image is represented as a column vector where each scalar is the mean of all corresponding pixels of the training images. Whenever the two dataset having the same mean is considered then there exists some problem (how to differ the two datasets). The difference between these two dataset is a measure of how spread the data is. It is the average distance from the mean of the data point to a point.

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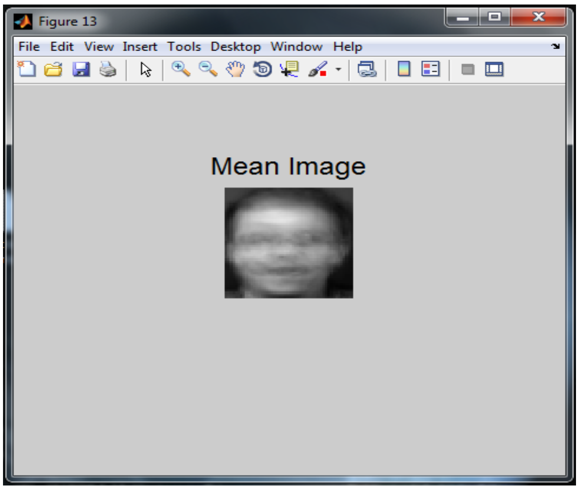

Fig 2 Mean Image

The next process is to create the Eigen space which is the reduced vectors of the mean normalized training face images. Once the training face images are centered, the next process is to create the Eigen space which is the reduced vectors of the mean normalized training face images.A matrix is said to be defective if it fails to have n linearly independent eigenvectors. The distance-computation steps are formulated as convex optimization problems over the space of blur kernels. Thus with each gallery image can associate a corresponding convex set., All defective matrices have fewer than n distinct eigenvalues, but not all matrices with fewer than n distinct eigenvalues are defective.Eigen faces is the name given to a set of eigen vectors when they are used in the computer vision problem of human recognition. The eigen vectors are derived from the covariance matrix of the probability distributions over the high dimensional vector space of images. The eigen faces themselves form a basis set of all images construct the covariance matrix. This produces dimension reduction allowing the smaller set of basis images to represent the original training images.

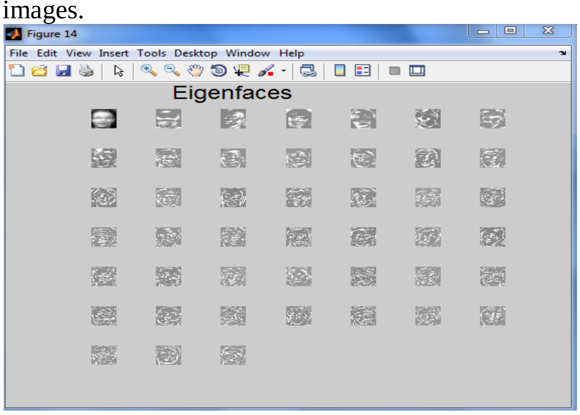

Fig 5 Eigen Faces

B. Feature Extraction Using LDA

To use Linear Discriminant Analysis in order to obtain a compact and discriminative feature representation.To reduce the dimensionality of feature vector so that a discriminant and compact representation can be achieved. Linear Discriminant Analysis (LDA) is used for this purpose. LDA is a statistical approach for supervised dimensionality reduction and classification which has been widely used on face recognition

III. CLASSIFICATION ALGORITHM

Classification is the actual recognition process. The feature vector obtained from the feature extraction is matched to classes (persons) of facial images already enrolled in a database.

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1. *Direct Recognition of Blurred Faces (DRBF)*

The set of all images obtained by blurring a given image forms a convex set, and more specifically, this set is the convex hull of shifted versions of the original image. Thus with each gallery image can associate a corresponding convex set., propose a blur-robust face recognition algorithm. In the basic version of our algorithm, we compute the distance of a given probe image from each of the convex sets, and assign it the identity of the closest gallery image. The distance-computation steps are formulated as convex optimization problems over the space of blur kernels. it can be easily incorporated into our algorithm, resulting in improved recognition performance. Further, make our algorithm robust to outliers and small pixel miss-alignments by replacing the Euclidean distance by weighted L_1-norm distance and comparing the images in the LBP (local binary pattern) space.To incorporate this fact we divide the face image into different regions and weigh them differently when computing the distance between probe image I_b and gallery sets $\mathcal{B}_j$

$$r_j = \min_h \|W(i_b - A_j)\|_2^2$$
$$\text{s,t,} \quad h \geq 0, \quad \|h\|_1 = 1 \quad C(h) = 0 \qquad (1)$$

To make our algorithm robust to outliers, which could arise due to variations in expression, we propose to replace the L_2norm in by the L_1norm

$$h_j = \arg\min_h \|W(i_b - A_j)\|_1$$
$$\text{s,t,} \quad h \geq 0, \quad \|h\|_1 = 1 \quad C(h)=0 \qquad (2)$$

Note that the above optimization problem is a convexL_1-norm problem, which we formulate and solve as a Linear Programming(LP) problem

2.Illumination-Robust Recognition of Blurred Faces (IRBF)

The major computational step of the algorithm is the optimization problem of which is a non-convex problem. To solve this problem we use an alternation algorithm in which we alternately minimize over h and α_m. i.e. in one step we minimize over h keeping $\alpha_m$fixed and in the other step we minimize over $\alpha_m$keeping h fixed and we iterate till convergence.

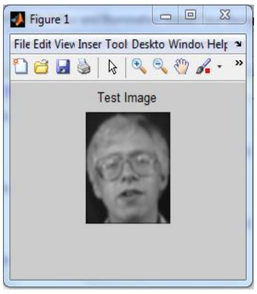
Each step is now a convex problem: the optimization over h for fixed $\alpha_m$reduces to the same problem asand the optimization of α given h is just a linear least squares problem. The complexity of the overall alternation algorithm is O(T (N + K3)) where T is the number of iterations in the alternation step, and O(N) is the complexity in the estimation of the illumination coefficients. We also propose a robust version of the algorithm by replacing the L_2-norm in (3.14) with the L_1-norm

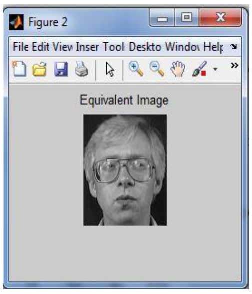
$$[h_j, \alpha_j, m] = \arg\min_{h,\alpha_m} \left\| W\left(i_b - \sum_{m=1}^{9} \alpha_m A_{j,m} h\right)\right\|_1 \qquad (3)$$

Again, this is a non-convex problem and we use the alternation procedure which reduces each step of the algorithm to a convex L_1-norm problem. We formulate these L_1 -norm problems as Linear Programing (LP) problems. The complexity of the overall alternation algorithm is O(T (N3 + (K + N)3)). The algorithm is summarized in Algorithm 2.

The major computational step of the algorithm is the optimization problem of (3.14), which is a non-convex problem. To solve this problem we use an alternation algorithm in which we alternately minimize over h and α_m. i.e. in one step we minimize over h keeping α_m fixed and in the other step we minimize over $\alpha_m$keeping h fixed and we iterate till convergence. Each step is now a convex problem: the optimization over h for fixed α_m reduces to the same problem as and the optimization of α given h is just a linear least squares problem.

Fig. shows the output window for the Robust Face Recognition using variations in Blur and Illumination. Face recognition system is a computer application for automatically identifying or verifying a person from a digital image. One of the ways to do this is by comparing selected facial features from the image and a facial data base. Face Recognition has been a very popular topic in pattern recognition community because of its numerous technical challenges and commercial applications.The recognition of faces is very important for many applications: video-surveillance, retrieval of an identity from a data base for criminal investigations and forensic applications.





IV. CONCLUSION

Motivated by the problem of remote face recognition, addressed the problem of recognizing blurred and poorly illuminated faces. The efficacy of our algorithms in tackling the challenging problem of face recognition in uncontrolled settings That the set of all images obtained by blurring a given image is a convex set given by the convex hull of shifted versions of the image. Based on this set-theoretic characterization, This proposed a blur-robust face recognition algorithm DRBF. Again, this is a non-convex problem and we use the alternation procedure which reduces each step of the algorithm to a convex L_1-norm problem In this algorithm we can easily incorporate prior knowledge on the type of blur as constraints. Using the low-dimensional linear subspace model for illumination, we then showed that the set of all images obtained from a given image by blurring and changing its illumination conditions is a bi-convex set, we proposed a blur and illumination robust algorithm IRBF.

REFERENCES

[1] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition A literature survey," ACM Comput.Surv., vol. 35, no. 4, pp.399–458, Dec. 2003.

[2] J. Ni and R. Chellappa, "Evaluation of state-of-the-art algorithms forremote face recognition," in Proc. IEEE 17th Int. Conf., Image Process., Sep. 2010, pp. 1581–1584.

[3] M. Nishiyama, A. Hadid, H. Takeshima, J. Shotton, T. Kozakaya, and O. Yamaguchi, "Facial deblur inference using subspace analysis for recognition of blurred faces," IEEE Trans. Pattern Anal. Mach. Intell.,vol. 33, no. 4, pp. 838–845, Apr. 2011

[4] D.Kundur and D.Hatzinakos, "Blind image deconvolution revisited."

[5] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, "Understanding blind deconvolution algorithms," IEEE Trans. Pattern Anal. Mach. Intell.,vol. 33, no. 12, pp. 2354–2367, Apr. 2011.

[6] T. Ojala, M. Pietikäinen, and T. Mäenpää,"Multiresolution gray-scaleand rotation invariant texture classification with local binary patterns," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no.7,pp.971–987,Jul. 2002.

[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] R. Ramamoorthi and P. Hanrahan, "A signal-processing framework for reflection," ACM Trans. Graph., vol. 23, no. 4, pp. 1004–1042, 2004.

[9] K.-C. Lee, J. Ho, and D. J. Kriegman, "Acquiring linear subspaces forface recognition under variable lighting," IEEE Trans. Pattern Anal.Mach. Intell., vol. 27, no. 5, pp. 684–698, May 2005.

[10] H. Hu and G. De Haan, "Adaptive image restoration based on localrobust blur estimation," in Proc. Int. Conf. Adv. Concep. Intell. Vis. Syst.,2007, pp. 461–472.

[11] W. H. Richardson, "Bayesian-based iterative method of image restoration,"J. Opt. Soc. Amer., vol. 62, no. 1, pp. 55–59, Jan. 1972.

[12] A. Levin, "Blind motion deblurring using image statistics," in Proc. Adv.Neural Inform. Process. Syst. Conf., 2006, pp. 841–848.

[13] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman,"Removing camera shake from a single photograph," in Proc. ACM SIGGRAPH Conf., 2006, pp. 787–794.

[14] T. Ahonen, E. Rahtu, V. Ojansivu, and J. Heikkilä, "Recognition ofblurred faces using local phase quantization," in Proc. 19th Int. Conf. Pattern Recognit., Dec. 2008, pp. 1–4.

[15] R. Gopalan, S. Taheri, P. K. Turaga, and R. Chellappa, "A blur-robustdescriptor with applications to face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 6, pp. 1220–1226, Jun. 2012.

[16] V.Ojansivu and J. Heikkilä, "Blur insensitive texture classification usinglocal phase quantization," in Proc. 3rd Int. Conf. Image Signal Process.,2008, pp. 236–243.

[17] I.Stainvas and N. Intrator, "Blurred face recognition via a hybridnetwork architecture," in Proc. Int. Conf. Pattern Recogn., 2000,pp. 809–812.

[18] H. Zhang, J. Yang, Y. Zhang, N. M. Nasrabadi, and T. S. Huang, "Closethe loop: Joint blind image restoration and recognition with sparse representation prior," in Proc. IEEE Int. Conf. Comput. Vis., Nov. 2011, pp. 770–777.

[19] P. Combettes, “The convex feasibility problem in image recovery,” inProc. Adv. Imag. Element. Phys., 1996, pp. 155–270.

[20] H. Trussell and M. Civanlar, “The feasible solution in signal restoration,”IEEE Trans. Acoust., Speech Signal Process., vol. 32, no. 2,pp. 201–212, Apr. 1984.

[21] P. Combettes and J. Pesquet, “Image restoration subject to a total variation constraint,” IEEE Trans. Image Process., vol. 13, no. 9, pp.1213–1222, Sep. 2004.

[22] H. Wang, S. Li, Y. Wang, and J. Zhang, “Self quotient image forface recognition,” in Proc. Int. Conf. Image Process., Oct. 2004,pp. 1397–1400.

[23] B. Kumar, M. Savvides, and C. Xie, “Correlation pattern recognitionfor face recognition,” Proc. IEEE, vol. 94, no. 11, pp. 1963–1976, Nov.2006.

[24] M. Savvides, B. V. K. V. Kumar, and P. K. Khosla, “Eigenphases vseigenfaces,” in Proc. Int. Conf. Pattern Recognit., vol. 3. 2004,pp. 810–813.

[25] R. Gross and V. Brajovic, “An image preprocessing algorithm forillumination invariant face recognition,” in Proc. 4th Int. Conf. Audio-Video-Based Biometr. Person Authent., 2003, pp. 10–18.