

An Approach For Unconstrained Face Recognition Algorithm Using Computer Vision Method

Faizal Y¹, Konguvel E²

¹(PG Student, Dhanalakshmi Srinivasan College of Engineering, Coimbatore)

²(Assistant Professor, Dhanalakshmi Srinivasan College of Engineering, Coimbatore)

ABSTRACT : This address the difficulty of unconstrained face recognition from vaguely acquired images. The main factors that make this difficulty challenging are image dilapidation due to blur, and appearance variations due to illumination and pose. In this paper, we deal with the problems of blur and illumination. We demonstrate the set of all images obtained by blurring a given image forms a convex set. Based on this set theoretic classification, we suggest a blur-robust algorithm whose main step involves solving simple convex optimization troubles. We do not suppose any parametric form for the blur kernels, however, if this information is obtainable, it can be simply integrated into our algorithm..

Keywords – Direct recognition of blurred and illuminated faces, remote biometrics, unconstrained face recognition.

1. INTRODUCTION

FACE recognition has been an intensely researched field of computer vision for the past couple of decades [1]. Though significant strides have been made in tackling the problem in controlled domains (as in recognition of passport photographs) [1], significant challenges stay behind in solving it in the unconstrained domain. One such situation occurs while recognizing faces acquired from outlying cameras. The main factors that make this a exigent problem are image degradations due to blur and noise, and variations in appearance dueto illumination and pose [2] (see Figure 1.).



Fig.1. Face images captured by a distant camera in unconstrained settings. The main challenges in recognizing such faces are variations due to blur, pose, and illumination. In this paper, we specifically address the problems of blur and illumination.

In this document, we purposely address the difficulty of recognizing faces across blur and illumination. A noticeable approach to recognizing blurred faces would be to deblur the image first and then distinguish it using traditional face recognition techniques [3]. However, this approach involves solving the challenging problem of blind image deconvolution [4], [5]. identity of the closest gallery image Further, we make our algorithm robust to outliers and small pixel mis-alignments by replacing the Euclidean distance by weighted $L1$ -norm distance and comparing the images in the LBP (local binary pattern) [6] space. convex sets, and assigns it the identity of the closest gallery image.

2. COMPUTER VISION

FACE recognition has been an intensely researched field of computer vision for the past couple of decades. Though significant strides have been made in tackling the problem in controlled domains (as in recognition of passport photographs), significant challenges remain in solving it in the unimpeded domain. One such situation occurs while recognizing faces acquired from far-away cameras. The main factors that make this

a demanding difficulty are image degradations due to blur and noise, and variations in appearance due to illumination and pose we specifically deal with the problem of recognizing faces across blur and illumination. incorporated into our algorithm, ensuing in better recognition performance.

2.1 Standard Demonstration Of A Face Recognition System:

FACE recognition has become a very vigorous area of study in recent years mainly due to increasing security demands and its potential commercial and lawenforcement applications. In the first phase, the 2D-DCT for every face image is computed, and characteristic vectors are created from the discrete cosine transform (DCT) coefficients. The second phase uses a self-organizing map (SOM) with an unconfirmed learning method to classify vectors into groups to recognize if the subject in the input image is “present” or “not present” in the image database. If the theme is classified as present, the finest match image found in the preparation database is displayed as the end result, else the result displays that the subject is not found in the image database.

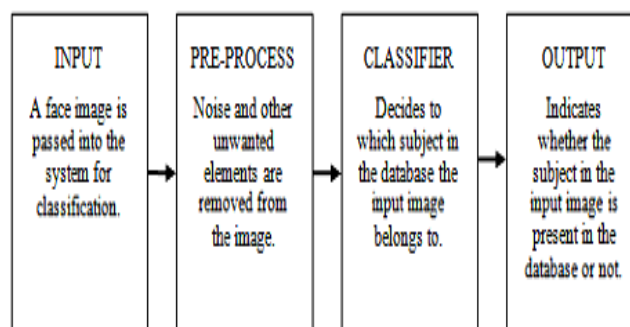


Fig 2 Block diagram for face recognition system

2.2 Voila Jones Technique

The Three main contributions/phases of the algorithm:

- Characteristic extraction
- Classification by boosting
- Multi-scale recognition algorithm

Feature extraction and feature estimation.

- Rectangular features are used, with a novel image depiction their calculation is very fast.

Classifier preparation and feature selection using a slight variation of a technique called AdaBoost.

2.3 Feature Extraction

The Features are extracted from sub windows of a model image. The support size for a sub window is 24 by 24 pixels. Each of the four feature types are scaled and shifted across all probable combinations. In a 24 pixel by 24 pixel sub window there are ~160,000 possible features to be intended.

2.4 Learning with many Features

By Learn a single easy classifier. Categorize the data. Look at where it makes errors. Now learn a 2nd effortless classifier on the weighted data. Study a 3rd classifier on the weighted data and so on until we study T simple classifiers. Last classifier is the combination of all T Classifiers. This process is called “Boosting” – works very well in practice.

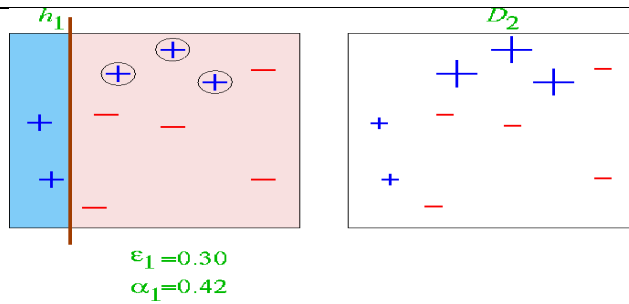


Fig. 4 First classifiers

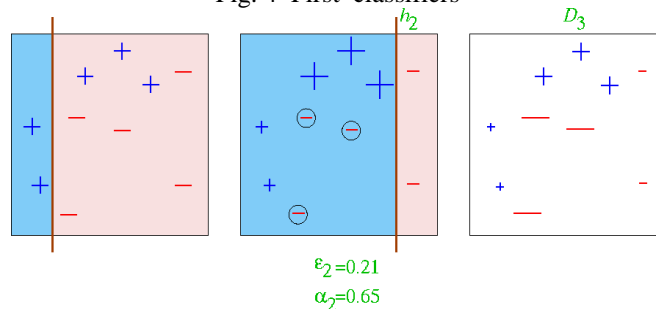


Fig. 5 First 2 classifier

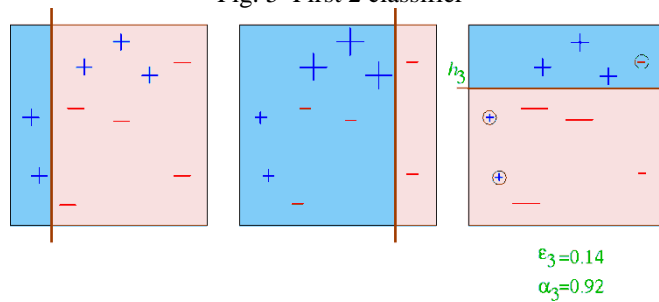


Fig. 6 First 3 classifiers

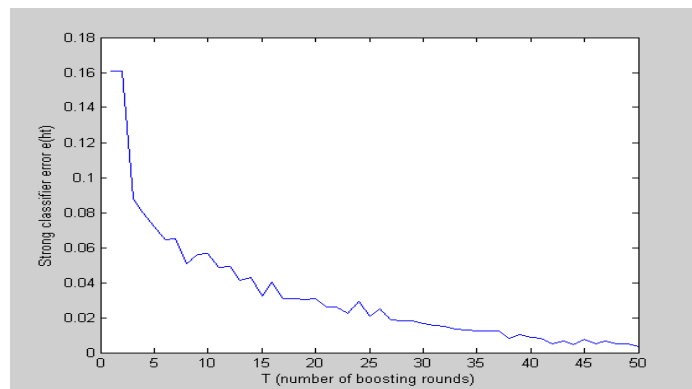


Fig. 8 reduction in error as boosting ADDS classifiers

2.5 Face recognition system arrangement

The A common face recognition system The key in of a face recognition system is always an image or video stream. The yield is an identification or verification of the subject or subjects that emerge in the image or video. Some approaches define a face recognition scheme as a three step procedure .From this point of sight, the Face Detection and Feature Extraction phases could run concurrently.



Fig 10 face recognition system structure

Face detection is defined as the method of extracting faces from scenes. So, the system positively identifies a definite image region as a face. This process has many applications like face tracking, pose estimation or com-pression. The next step -feature extraction- involves obtaining related facial features from the data. These features could be firm face regions, variations, angles or measures, which can be individual relevant (e.g. eyes spacing) or not. This phase has other applications similar to facial feature tracking or emotion recognition. Lastly, the system does identify the face. In an identification assignment, the system would report an identity from a database. This stage involves a comparison method, a classification algorithm and an correctness measure. This phase uses methods general to many other areas which also do some classification process -sound engineering, data removal et al. These phases can be compound, or new ones could be added. Therefore, we could find many unusual engineering approaches to a face recognition problem.

2.6 Face detection problem arrangement

Face Detection is a notion that includes many sub-problems. Some systems notice and locate faces at the same time, others first execute a detection routine and then, if positive, they try to find the face.

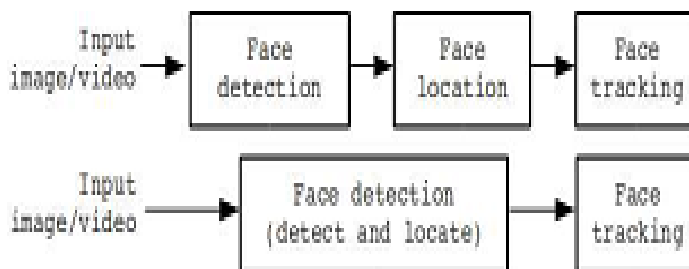


Fig 10 face detection problem structure

Face detection algorithms typically share general steps. Initially, some data dimension reduction is done, in order to achieve a admissible response time. Some pre-processing could also be done to adapt the input image to the algorithm prerequisites. Then, some algorithms examine the image as it is, and some others attempt to extract certain applicable facial regions. The next phase typically involves extracting facial features or measurements.

Image at left has a higher pixel count than the one to the right, but has lower resolution. The resolution of a digital camera is often restricted by the image sensor ^[5] (typically a CCD or CMOS sensor chip) that turns light into discrete signals. The sensor is made up of millions of "buckets". The brighter the image at a given point on the sensor, the better the value that is read for that pixel. Depending on the physical arrangement of the sensor, a color filter array may be used which requires a demosaicing. The number of resulting pixels in the image determines its "pixel count".

3. TEST RESULTS

Evaluate the proposed algorithms: the “blur-only” formulation LBP of section II and the “blur and illumination” formulation Viola Jones method of section III on synthetically blurred datasets- FERET and PIE, and a real dataset of distantly acquired faces with considerable blur and illumination variations which we will refer to as the REMOTE dataset, see Figure 1. In section IV-A, we appraise the performance of the LBP algorithm in recognizing faces blurred by unusual types and amounts of blur. In section IV-B, we evaluate the efficiency of the Viola Jones technique algorithm in recognizing blurred and poorly illuminated faces. Lastly, in section IV-A, we estimate our algorithms, LBP and Viola Jones technique, on the real and demanding dataset of REMOTE.

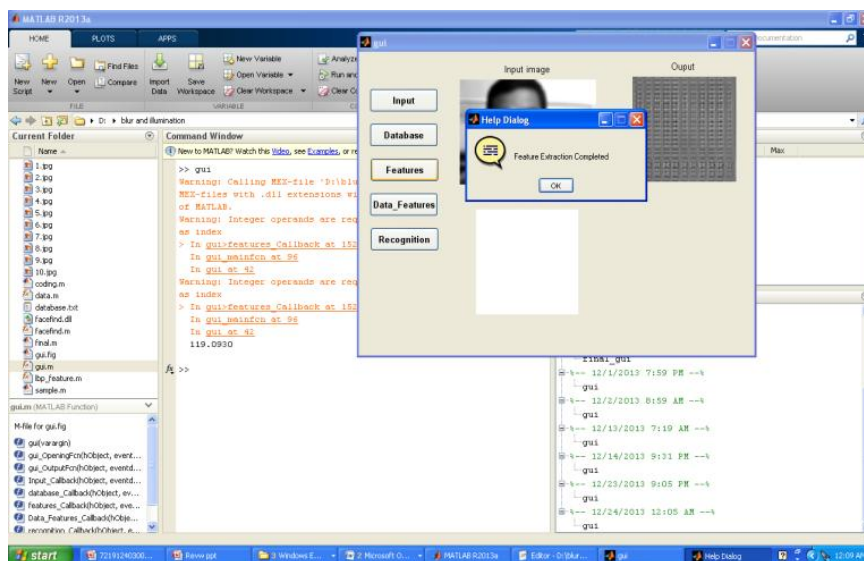


Fig 11 Data Feature Completion

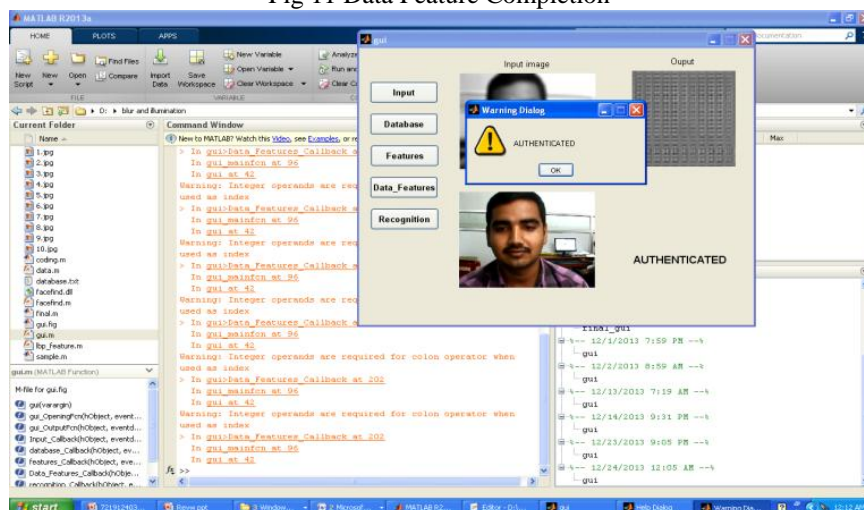


Fig 12 The Person Authenticated Or Unauthenticated

4. CONCLUSION

Aggravated by the problem of remote face recognition, we have addressed the problem of recognizing blurred and poorly illuminated faces. We have revealed 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 classification, we projected a blur-robust face recognition algorithm LBP. In this algorithm we can simply incorporate prior information on the type of blur as constraints. Using the low-dimensional linear subspace representation for illumination, we then showed that the set of all images obtained from a given image by blurring and varying its illumination conditions is a bi-convex set. Again, based on this set-theoretic classification, we proposed a blur and illumination robust algorithm Viola Jones technique. We also confirmed the efficacy of our algorithms in tackling the challenging problem of face recognition in unrestrained settings. Our algorithm is based on a generative model followed by nearest-neighbor classification between the query image and the gallery space. Hence we consider that incorporating a discriminative-learning based approach like SVM into this formulation would be a very capable direction for future work. We would also like to model pose-variation under the similar framework.

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 for remote 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.