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Face Recognition using Features from Accelerated Segment Test for Invariance Towards Changes in Illumination

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ABSTRACT

The area of face recognition in spite of being the most unobtrusive biometric authentication methodology has enjoyed limited application is real world owing to constant changes that occur on the face due to various factors. The changes brought about on a face image due to variations in the illumination have been known to be a major contributor towards tremendous changes in the image which render any face recognition system of little practical use. This paper presents a new technique to address this issue by identifying robust illumination invariant fiducial points from the face so that changes in the parameters of illumination do not impact the crucial information in a face image and thus make the face recognition system stronger and usable in practice. We have made the use of Features from Accelerated Segment Test (FAST) for detecting the interest points in the face images from the training and the test data sets. It identifies those fiducial points in a face image which are located at well-defined positions irrespective of changes happening in the image due to variations in illumination. The technique is also computationally far more efficient than various other standard methods that have been used so far for feature extraction. Using nearest neighbour search strategy, each fiducial point in the test feature vector is compared with the fiducial points in every training feature vector. The maximum number of matches between the test and the training feature vectors leads to a possible match. FAR and FRR for the method were observed to showcase encouraging results in authenticating faces even in presence of extreme variations in illumination conditions which supports the use of FAST features for designing face recognition methodologies that are significantly invariant to the changes in illumination.

Keywords : Fiducial points, Features from Accelerated Segment Test, NNS, FAR, FRR, DCT, Homomorphic filtering

I. INTRODUCTION

Biometric access control has laid a foundation for highly secure recognition and verification solutions. It enables authenticating the identity of a person based on morphological, physiological or behavioural characteristics. The reason for its success is the fact that unlike keys or passwords, these personal traits are difficult to lose, forget or copy and are therefore safer and more secure than keys or passwords. The primary biometric modalities are Fingerprints, Face, Iris, Retina, Palm print, Ear, Veinous flow, Hand Geometry and Voice. However face and ear are the least obtrusive of all. Face biometrics have become popular over the last decade for being the least intrusive and fastest biometric technology which prevents people to falsify or assume other people's identities. It can be equally effective be it a still or a video image of a scene. The primary need of using Face as a modality for recognition is its discreetness and non-intrusiveness. It does not need people to place their hand over a scanner or precisely position eye in front of a reader as face recognition systems can unobtrusively take pictures of people's faces when they are present in a defined area. There is no intrusion or delay, and in most cases the subjects are entirely unaware of the process/surveillance.

Humans have the capability of accurately recognizing people using their facial information both in static and dynamic context. They possess the ability to precisely recognize individuals even in presence of variations due pose, expression, emotion, illumination, ageing, facial distraction like hair growth, makeup etc. These observations lead us towards the development of face recognition systems which could have performance as high as humans deliver [1]. The area of face recognition in biometrics is therefore centred on the development of such systems which can recognise a person based on the facial characteristics and achieve highest possible robustness against the variations owing to the aforementioned factors. Such a system needs to be swift and accurate at the same time and possess reasonable resilience too.

Various computational models for face recognition have been designed in the past. The most significant initial achievement in the area of face recognition was the Eigen Face methodology, proposed by M.A.Turk & A.P.Pentland [2] [3]. The use of FLDA in place of PCA in this method gave rise to the technique of face recognition using Fisher faces [4] which is analogous to Eigen faces produced by the PCA method. Independent Component Analysis [5] and Probabilistic LDA have also been used for face biometrics and are reasonably efficient. Face recognition using Fuzzy c-Means clustering and sub-NNs was developed by Lu J, Yuan X and Yahagi T [6]. Apart from these one may find various other approaches which are based on different methods of feature extraction and classification like using Neural networks [7], SVM [8] [9] etc. Varying degrees of success has been achieved with each one of the face recognition methodologies developed so far [10]. However their performance in an uncontrolled environment is of a concern because the variations in various factors like pose, expressions, emotions, illumination, facial distractions like hair growth, makeup, spectacles and age cause dramatic alterations in the appearance of a face image. The effect becomes even more pronounced when these variations occur together. Thus there is a need to develop a face recognition system which can encompass various efficient methodologies to deal with these inevitable changes in the appearance of face and its impact on face image.

This paper presents technique to counter the effects of illumination variance which is one the major hurdles in designing high performance face recognition system. It is capable of producing drastic changes in the face appearance due to varying intensity of illumination, direction and energy distribution. These variations severely affect an image due to unavoidable changes in shadowing and shading parameters which bring about variations in the global and local features of the face and force the results towards incorrectness. Such kinds of variations may also at times be more pronounced than other variations in the facial characteristics of an individual. Various techniques have been proposed in the past to incorporate illumination invariance in face recognition. The major factors which determine the applicability of any such technique in practice are the success rate and the computational efficiency. Histogram equalization is known to be effective in reducing the impact of changes in illumination [11]. Xie and Lam [12] have proposed a method for normalizing the illumination by dividing the face into a set of triangular facets and thereafter normalize the intensity values within each facet to be of zero mean and unit variance. Short et al. [13] did the comparison of five photometric normalization methods, namely illumination insensitive Eigen spaces, multi scale Retinex method, homomorphic filtering, isotropic smoothing and anisotropic smoothing methods. Chen et al. [14] employed DCT to compensate for illumination variation in the logarithm domain. It has been found observed that histogram equalization with anisotropic smoothing method as photometric normalization produced the best results. Hallinan [15] proposed a methodology that showed that five Eigen faces were sufficient to represent the face images under a wide range of lighting condition. Zhao and Chellappa [16] proposed a method based on Symmetric Shape from Shading to accomplish the same. It was based on the symmetry and shape similarity of faces. Photometric Alignment approach was used by Shashua [17] to find the algebraic connection between all images of an object taken under varying illumination conditions. Savvides et al. [18] applied Eigen faces in phase domain and created an approach called as Eigen phase which reasonably enhanced the performance of illumination invariant recognition. Local Binary Pattern (LBP) [19] [20] that can be used to describe the intensity relationship between a pixel and its neighbours, has been found to be an illumination invariant local feature. Relative Image Gradient feature was utilised by Wei and Lai [21] and Yang et al. [22] for designing face recognition methodology invariant to changes in lighting. Zhang and Samaras [23] proposed technique for face recognition under arbitrary unknown lighting by using the spherical harmonics representation. Gao and Leung [24] proposed line edge map for face recognition by. The edge pixels were grouped into line segments followed by use of Hausdorff Distance to measure the similarity between two line segments.

The paper discusses a methodology to design an illumination invariant face recognition system by using Features from Accelerated Segment Test (FAST) [25] to detect a set of robust features from face images which are invariant to changes in illumination. The method yields significantly high performance with much less computational cost involves as compared to other standard methods. The maximum number of matches between the test and the training feature vectors leads to a possible match.

The rest of this paper is organizes follows : Section II discusses the conceptual details of Features from Accelerated Segment Test (FAST) method for identifying robust features from an image. Section III describes the proposed methodology of applying FAST for designing illumination invariant face recognition system. Details of the experimental results have been presented in Section IV. Conclusions and future scope have been elaborated in Section V.

II. OVERVIEW OF METHODOLOGY

FAST algorithm was proposed by Edward Rosten and Tom Drummond [25] for identification of the interest points in an image.

An interest point in an image is a pixel which has a well-defined position and can be robustly detected. FAST is a corner detection method and it is computationally much more efficient than any of the commonly used algorithms.

A basic algorithm to detect the features using FAST technique is:

1. Let the intensity of a candidate pixel p be Ip.
2. Set a threshold intensity value T.
3. Mark a Bresenham circle of radius which consists of 16 pixels that surround the given pixel p.
4. Label each pixel in the circle from 1 to 16 moving in clockwise order.
5. Compare the intensity of the pixels 1, 5, 9 and 13 of the circle with Ip and check whether at least three of the four pixel values I_1, I_5, I_9 and I_{13} are above or below Ip by the value T. If not then go to step 5a else 5b.

5a. Reject the candidate pixel p and do not consider it as a feature, go to step 6.

5b. Compare the intensities of all the remaining pixels and classify the pixel as a feature if a set of N (<12) contiguous pixels out of the 16 in the Bresenham circle is either above or below Ip by the value T.

6. Repeat the procedure for all the pixels in the image.

This yields a set of all the interest points in an image which can be used for object tracking, recognition, matching, surveillance and other purposes.

III. PROPOSED METHODOLOGY

We present a method for illumination invariant face recognition using Features from Accelerated Test (FAST) algorithm for detection of the fiducial points from a face image.

Prior to feature extraction, it is necessary that face images in both the training and the testing data sets are pre-processed to elevate the overall performance of face recognition and to neutralise effects of changing illumination conditions on the face images. The images are first of all subject to illumination normalization to reduce some of the effects of illumination variations. Discrete Cosine Transform normalization is applied over the face images, which is followed by Histogram Equalization. It is the most common histogram normalization or grey level transform used to increase the local contrast of object in the image. It produces an image with equally distributed brightness levels over the whole brightness scale thereby modifying the dynamic range of the image thereby normalizing the illumination of the image. Homomorphic filtering [26] is applied for simultaneous brightness range compression and enhancement of the contrast of the face images.

Thereafter FAST algorithm is applied over the normalised face images in both the data sets. To detect the features from the image, the algorithm runs over all the picture elements of the image. It identifies whether a pixel p in the image can be considered to be a feature or should it be discarded.

We have used a variant of the FAST algorithm which encompasses a machine learning approach [27] to detect the illumination invariant fiducial points from the face images.

1. Consider a training data set of images.
2. Run the FAST algorithm over every image to detect which pixels can be considered as the features.
3. For every pixel p, create a feature vector holding the 16 pixel values that surround.
4. Repeat for all the pixels in all the images generating a final vector V for the data obtained at step 3 for all the images.
5. Each value in the vector, can assume three states.
   i. S_d : Darker than p, if $Ip \rightarrow x \leq Ip - T$
   ii. S_b : Brighter than p, $Ip \rightarrow x \geq Ip + T$
   iii. S_s : Similar to p, if $Ip - T \leq Ip \rightarrow x \leq Ip + T$

   Where, $Ip \rightarrow x$ is the pixel intensity of pixel x.
6. Depending on the states the entire vector V is divided into three subsets, V_d, V_s and V_b.

   $V_d = \{p \in V : Sp \rightarrow x = d\}$ **(1)**

   $V_s = \{p \in V : Sp \rightarrow x = s\}$ **(2)**

   $V_b = \{p \in V : Sp \rightarrow x = b\}$ **(3)**

   Where, $Sp \rightarrow x$ is the state.
7. Let Kp be a boolean variable which if true indicates p as feature and vice versa.
8. Using ID3 algorithm, query each subset using the variable Kp to find the true class of pixels. Based on the principle of entropy minimization, query the 16 pixels in such a way that the true class is found with minimum number of queries.
9. For a set of pixels V, find the entropy H(V) given by:

   $(c+n)\log_2(c+n) - c\log_2 c - n\log_2 n$ **(4)**

   such that,

   c: number of corners

   $c = \{i \in V: K_i \text{ is true}\}$ **(5)**

   n : number of non-corners

   $n = \{i \in V: K_i \text{ is false}\}$ **(6)**
10. Compute the Information Gain Hg:

    $Hg = H(V) - H(V_b) - H(V_s) - H(V_d)$ **(7)**
11. Recursively apply the process of entropy minimization as described in step 7 to all the three subsets, V_d, V_s and V_b.
12. Terminate the process when entropy of a subset is zero.
13. Apply the order of querying which is learned by the decision tree for detection of features in all the images.

The features thus derived from the facial image using FAST technique act as the fiducial points for that face.

The features are saved in a two dimensional vector, where the number of rows define the number of fiducial points and columns represent the location of the pixel coordinates.

Once all the fiducial points are calculated using FAST algorithm for both the training and testing data sets, the classification of the test faces is done by matching the features.

Each fiducial point in the test feature vector $F_{\textbf{Test}}$ is compared with the fiducial points in every training feature vector $F_{\textbf{Train}}$. The maximum number of matches between the test and the training feature vectors leads to the possible result, which is however, first checked for being a false positive.

Feature matching is done using NNS (Nearest Neighbour Search). For a given set S of points in a d-dimensional metric space D and a query point q ∈ D, we find the nearest point in S to q by measuring the Euclidean distance in between them.

$$d(u, v) = \left(\sum_i (u_i - v_i)^2 \right)^{0.5} \quad \textbf{(8)}$$

1. Create a match vector $M_{\textbf{Train}}$ for every training image to hold the number of matches between the training and test image fiducial points.
2. For every fiducial point in the test feature vector $F_{\textbf{Test}}$ of the test image, its Euclidean distance to all the fiducial points in every training feature vector $F_{\textbf{Train}}$ of the training image is computed.
3. The fiducial point in each training feature vector $F_{\textbf{Train}}$ with the least Euclidean distance to the current test fiducial point in $F_{\textbf{Test}}$ is marked as the best match for it from $F_{\textbf{Train}}$.
4. The Euclidean distances of the best matches from all the training feature vectors are compared and the one with the least Euclidean distance is decided as the final match to the current test fiducial point in $F_{\textbf{Test}}$. Update the corresponding training match vector $M_{\textbf{Train}}$.
5. Find the NNDR (Nearest neighbour distance ratio) by comparing the distance to the best (d1) and the second best (d2) matching fiducial point, if the ratio between the both is above a threshold, then reject it as a false match.

   $$NNDR = d1/d2 \quad \textbf{(9)}$$

   If NNDR > 0.8, reject as false positive

6. Steps 2-5 are repeated for all the fiducial points in F_{Test}.
7. The training image with the matching vector M_{Train} having the maximum number of matches is identified as the resultant best match to the test image.

To find a match for a test subject in the database therefore needs identifying the maximum number of nearest neighbours in the vicinity of the test sample. The subject yielding maximum such values is decided as the best match for the test image.

IV. EXPERIMENTAL RESULTS

For ascertaining the accuracy of the proposed algorithm, Yale B Face database [28] has been used.

FAST features are identified for the test image and all the images in the training data set. Matching for the test image is done using Nearest Neighbour Search which yields a match if and only if it is present in the database. The database contains 5760 single light source images of 10 subjects each seen under 576 viewing conditions (9 poses x 64 illumination conditions). We use the 65 (64 illuminations + 1 ambient) images of a subject/pose for evaluating the proposed technique.

The technique has been compared with other standard methods to assess the performance in terms of accuracy, recognition rate, computational efficiency and training effort involved.

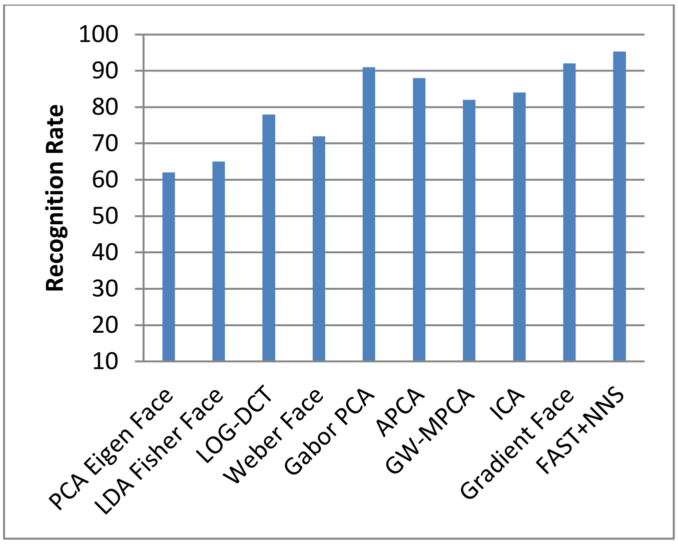

Figure 1. Comparison of Recognition Rate

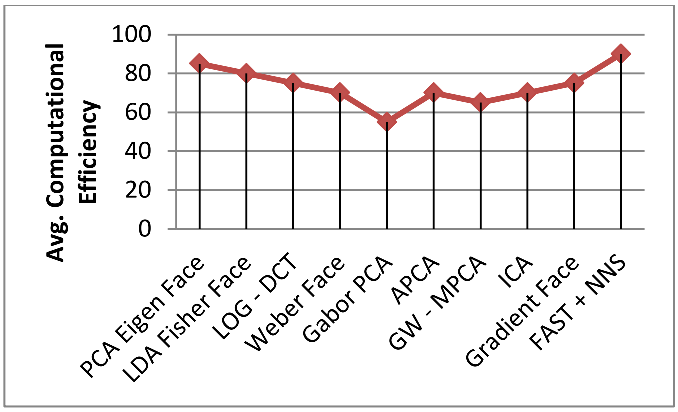

Figure 2. Computational Efficiency of various techniques (over uniform sized standard data sets from Yale B Face database.)

The proposed technique performed well when compared with other standard methods.

The parameters for recognition accuracy are based on FAR and FRR while the computational efficiency is measured in terms of the time and training effort spent. The technique has been compared for the parameters of performance and success rate with Principal Component Analysis based Eigen face strategy [2], Linear Discriminant Analysis based Fisher face method [4], Independent Component Analysis (ICA) [33], Weber face technique [30], Gradient Face [29] method, Gabor Kernel based PCA (Gabor PCA) [34], Adapted PCA [35], Gabor Wavelet based Modular PCA (GW-MPCA) [32] and LOG-DCT (Discrete Cosine Transform in Logarithm Domain) [31] methodologies.

V. CONCLUSION & FUTURE SCOPE

Usability of face recognition as a dependable biometric modality in controlled passive conditions has been extensively studied and developed. However it is the issue of practical applicability of face recognition in actual uncontrolled environment which has decelerated its use. Although face is the most discreet and natural method of recognition, the changes in illumination, pose, expressions, emotions, age, makeup and other facial distractions have been a major hurdle in its effective use. Various active and passive approaches have been designed to mitigate the issue. However to address the problem of high computational cost and performance, a novel method based on Features from Accelerated Segment Test and Nearest Neighbour Search has been proposed and evaluated. It not only delivers high success rate but does it with much less training and computational time involved.

The method can be integrated with a better classifier for even better results. FAST detects the robust facial features which are highly immune to changes in illumination. Such features when input to a strong classifier will further add to the performance. The approach may also be evaluated to explore its applicability in alleviating the impact of variations in expression, pose, makeup etc. which will enable us to lead towards an effective universal approach towards designing sturdy and robust face recognition system.

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