FACE VERIFICATION SYSTEM IN DIFFERENT ATMOSPHERIC CONDITIONS

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ABSTRACT

In the beginning stage, face verification is done using easy method of geometric algorithm models, but the verification route has now developed into a scientific progress of complicated geometric representation and matching process. In modern time the skill have enhanced face detection system into the vigorous focal point. Researcher's currently undergoing strong research on finding face recognition system for wider area information taken under hysterical elucidation dissimilarity. The proposed face recognition system consists of a narrative exposition-indiscreet preprocessing method, a hybrid Fourier-based facial feature extraction and a score fusion scheme. We take in conventional the face detection in unlike cheer up circumstances and at unusual setting. Image processing, Image detection, Feature- removal and Face detection are the methods used for Face Verification System (FVS). This paper focuses mainly on the issue of toughness to lighting variations. The proposed system has obtained an average of 81.5% verification rate on Two-Dimensional images under different lightening conditions.

Key Words: *Image processing, Image detection, Feature- removal and Face detection, Face Verification System (FVS)*

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1. INTRODUCTION

In the past decades, many appearance-based methods have been proposed to handle this problem, and new theoretical insights as well as good recognition results have been reported. In the proposed the verification of the face in different climatic conditions, this paper focuses mainly on the issue of robustness to lighting variations. Established advance for production with this concern can be broadly classified into three types based on look, normalized conditions, and quality methods. In direct appearance-based approaches, training examples are collected under different lighting conditions and directly (i.e., without undergoing any lighting preprocessing) used to learn a global model of the possible illumination variations but it requires a large number of training images and an expressive feature set, otherwise it is essential to include a good preprocessor to reduce illumination variations. Normalization based approaches seek to reduce the image to a more "canonical" form in which the illumination variations are suppressed. Histogram equalization is one simple example of this method. These systems are relatively helpful but their capability to switch spatially un-uniform dissimilarity ruins imperfect. The third advance method to pull out elucidation insensible characteristics sets straight from the given representation. These attribute sets range from geometrical skin texture to image copied features such as edge mapping, local binary pattern method (LBP), Gabor wavelet method, and neighboring autocorrelation filters. Although such facial appearance offer a immense step up on unprocessed gray image values, their conflict to the composite climatic deviation that happen in real-world face images is motionless reasonably incomplete. The integrative structure is projected, that combines the potentials of all three of the above systems. The generally progression can be viewed as a channel consisting of image normalization, feature extraction, and subspace representation, each stage increases resistance to illumination variations and makes the information needed for recognition more manifest. This method achieves very significant improvements, than the other method of verification rate is 88.1% at 0.1% false acceptance rate. Several aspects of the relationship between mage normalization and feature sets, Robust feature sets and feature comparison strategies, Fusion of multiple feature sets framework is the will be verified.

2. LITERATURE REVIEW

2.1 Principal Components Analysis (PCA)

There are two leading schemes to the features of face verifications problem: statistical based and view based. Numerous algorithms were produced PCA commonly referred to as the use of Eigen faces, is the technique With PCA, the probe and gallery images must be the same size and must first be normalized to line up the eyes and mouth of the subjects within the image. The PCA approach is then used to reduce the dimension of the data by means of data compression basics and reveals the most effective low dimensional structure of facial patterns. This reduction in dimensions removes information that is not useful and precisely decomposes the face structure into orthogonal components known as Eigen faces. Each face image may be corresponding to as the prejudiced sum of the Eigen faces, are stored up in a 1D arrangement. A survey representation is evaluated beside a gallery image by measuring the expanse between their individual quality vectors. The PCA method naturally requires the filled frontal face to be presented each time; otherwise the image results in poor performance. The primary advantage of this technique is that it can reduce the data needed to identify the individual to $1/1000^{th}$ of the data presented.

2.2. Linear Discriminant Analysis (LDA)

LDA is a statistical approach for classifying samples of unknown classes based on training samples with classes. This technique aims to maximize between-class variance and minimize within –class variance. In fig 2 where each block represents a class, there are large variances between classes, but little variance with in classes. When dealing with high dimensional face data, this technique faces the small sample size problem that arises where there are a small number of available training samples compared to the dimensionality of the sample space.

2.3. Elastic Bunch Graph Matching

EGBM relies on the concept that real face images have many non linear characteristics that are not addressed by the other linear methods, which includes variation in illumination, pose and expression. A Gabor wavelet transform creates a dynamic link architecture that projects the face onto an elastic grid. The Gabor jet is a node on the elastic grid notated by circles on the image below which describes the image behavior around a given pixel. It is the result of a convolution of the image with a Gabor filter, which is used to detect shapes and to extract features using image processing. Recognition is based on the similarity of the Gabor filter response at each Gabor node. The difficulty with this method is the requirement of accurate land mark localization which can sometimes be achieved by combining PCA and LDA methods.

2.4. Anisotropic Diffusion

In image processing and computer vision , anisotropic diffusion, also called Perona–Malik diffusion, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. Anisotropic diffusion resembles the process that creates a scale-space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Each of the resulting images in this family is given as a convolution c between the image and a 2D isotropic Gaussian filter, where the thickness of the strain boosted with the constraint. This distribution development is a linear and liberty invariant change of the innovative image. Anisotropic circulation is a simplification of this distribution method: it constructs a relative of parameterized images, but each resultant image is a arrangement among the unique representation and a filter that depends on the restricted content of the inventive image. As an effect, anisotropic dispersion is a non-linear and space-variant change of the original image. An image slope is a directional transform in the strength or color in an image. Image gradients may be used to pull out in sequence from images. Accurately, the grade of a two-variable function (here the image concentration function) is at each image end, a 2D vector with the mechanism given by the derived in the flat and perpendicular directions. At all image point, the slope vector points in the track of major probable concentration enlarge, and the duration of the slope vector be in contact to the rate of change in that track. Since the concentration function of a digital representation is only known at distinct points, derivatives of this role cannot be clear except we think that there is a fundamental constant intensity function which has been sampled at the image points. With some additional assumptions, the derivative of the continuous intensity function can be computed as a role on the sampled concentration purpose, i.e., the digital image. It turns out that the derived at any exacting point are functions of the strength values at almost all image points. However, approximations of these unoriginal functions can be distinct at slighter or better degrees of precision. The sobel operative represents a slightly incorrect estimate of the image gradient, but is still of enough excellence to be of realistic use in many applications. More specifically, it uses strength values only in a 3×3 section around each image point to near the matching image gradient, and it uses only numeral values for the coefficients which influence the image intensities to produce the slope estimate.

3. PROPOSED SYSTEM

3.1. Integral Normalized Gradient Image

We can make the following assumptions: 1) most of the intrinsic factor is in the high spatial frequency domain, and 2) most of the extrinsic factor is in the low spatial frequency domain. Considering the first assumption, one might use a high-pass filter to extract the intrinsic factor, but it has been proved that this kind of filter is not robust to illumination variations as shown. In addition, a high-pass filtering operation may have a risk of removing some of the useful intrinsic factor. Hence, we propose an alternative approach, namely, employing a gradient operation. The slope process is write as

$$\begin{aligned}\nabla\chi &= \nabla\left(\rho\sum_i \mathbf{n}^T\cdot\mathbf{s}_i\right)\\ &= (\nabla\rho)\sum_i \mathbf{n}^T\cdot\mathbf{s}_i + \rho\nabla\left(\sum_i \mathbf{n}^T\cdot\mathbf{s}_i\right)\\ &\approx (\nabla\rho)\sum_i \mathbf{n}^T\cdot\mathbf{s}_i = (\nabla\rho)W\end{aligned}$$

Where W=X*K the approximation comes from the assumptions that both the surface normal direction (shape) and the light source direction vary slowly across the image whereas the surface texture varies fast. The scaling factor is the extrinsic factor of our imaging model. The Retinex method and SQI method used the smoothed images as the estimation of this extrinsic factor. We also use the same approach to estimate the extrinsic part where is K a smoothing kernel and denotes the convolution. To overcome the illumination sensitivity, we normalized the slope map with the subsequent equation:

$$N = \frac{\nabla\chi}{\hat{W}} \approx \frac{(\nabla\rho)W}{\hat{W}} \approx \nabla\rho$$

After the normalization, the texture information in the normalized image

$N= \{Nx, N_y\}$ is still not apparent enough. In addition, the division operation may intensify unexpected noise terms. To recover the rich texture and remove the noise at the same time, we integrate the normalized gradients N_x and N_y with the anisotropic diffusion method which we explain in the following, and finally acquire the reconstructed image X_r

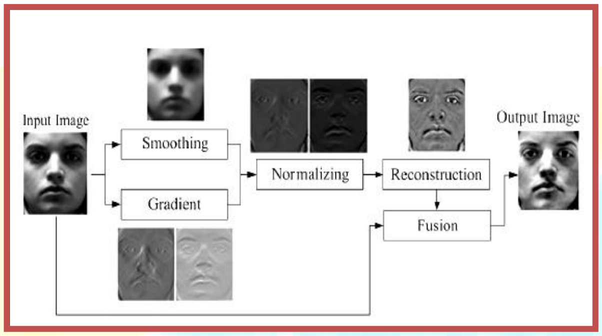

Fig 4: Structure of the integral normalized gradient image

3.2. Kernel Principle Component Analysis

KPCA encodes the pattern information based on second order dependencies, i.e., pixel wise covariance among the pixels, and are insensitive to the dependencies of multiple (more than two) pixels in the patterns. Since the eigenvectors in PCA are the orthonormal bases, the principal components are uncorrelated. In other words, the coefficients for one of the axes cannot be linearly represented from the coefficients of the other axes. Advanced arrange need in an image contain nonlinear associations surrounded by the pixel concentration values, such as the contact amid three or more pixels in a border or a arc, which can confine important information for recognition. Explicitly mapping the vectors in input space into higher dimensional space is computationally intensive. Using the kernel trick one can compute the higher order statistics using only dot products of the input patterns. The essential part of PCA has been functionally used to identify the face appliance and is experimentally to be capable to remove unwanted features from the image. The advantage of using KPCA over other nonlinear feature extraction algorithms can be significant computationally. KPCA does not require solving a nonlinear optimization problem which is expensive computationally and the validity of the solution as optimal is typically a concern. KPCA merely have need of the resolution of an eigenvalue difficulty. This reduces to using linear algebra to perform PCA in an arbitrarily large, possibly infinite dimensional, feature space. The kernel “trick” greatly simplifies calculations in this case.

An additional advantage of KPCA is that the number of components does not have to be specified in advance. KPCA is a useful generalization that can be applied to these domains where nonlinear features require a nonlinear feature extraction tool. We plan to use the KPCA algorithm on real earth science data such as the sea surface temperature (SST) or normalized difference vegetation index (NDVI).The resulting information from KPCA can be correlated with signals such as the Southern Oscillation Index (SOI) for determining relationships with the El Nino phenomenon. KPCA can be used to discover nonlinear correlations in data that may otherwise not be found using standard PCA. The information generated about a data set using KPCA captures nonlinear features of the data. These features correlated with known spatial-temporal signals can discover nonlinear relationships. KPCA offers improved analysis of datasets that have nonlinear structure.

3.3 Log-Likely hood Ratio for Score Fusion

We interpret the set of scores as a feature vector from which we perform the classification task. We have a set of scores $S_1 \ldots S_n$ computed by classifiers. Now the problem is to decide whether the query-target pair is from the same person or not based upon these scores. We can cast this problem as the following hypothesis testing:

$$\mathbf{H_0: S_1 \ldots S_n \sim p\,(s_{1,\ldots,}\ sn|diff)}$$

$$\mathbf{H_{1:}\ S_1 \ldots S_n \sim p\,(s_{1,\ldots,}\ sn|same)}$$

Where p ($s_{1,\ldots,}$ sn|diff) is the distribution of the scores when the query and target are from different persons, and p ($s_{1,\ldots,}$ sn|same) is the distribution of the scores when the query and target are from the same person. The figure gives example of such distributions and provides the intuition behind the benefits of using multiple scores generated by multiple classifiers. Suppose we have two classifiers and they produce two scores s_1 and s_2 and Figure shows **p (s_1 |diff)** and **p ($s_{1,}$ |same)** distributions of a single score. The region between the two vertical lines is where the two distributions overlap.

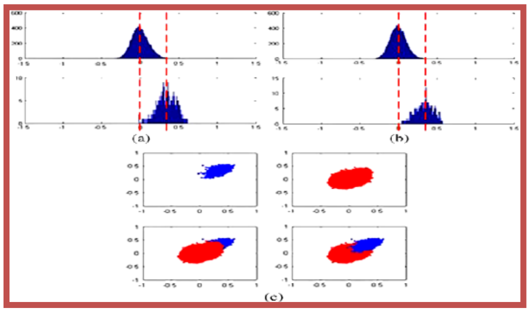

Fig 5: Score distribution of two classifiers

Intuitively speaking, a classification error can occur when the score falls within this overlapped region, and the smaller this overlapped region, the smaller the probability of classification error. Likewise, Fig. 9(b) shows **p (s_2 |diff) and p ($s_{2,}$ |same)** and. Fig(c) shows how the pair of the two scores ($s_{1,}$ s_2) is distributed. The upper left of Fig(c) is the scatter. Plot ($s_{1,}$ s_2) of when the query and target are from the same person and the upper right of Fig. 9(c) is the scatter plot of when the query and target are from different persons. The bottom of Fig(c) shows how the two scatter plots overlap. Compared with Fig. (a) and (b), we can see that the probability of overlap can be reduced by jointly considering the two scores s_1 ands$_2$ and , which suggests that hypothesis testing based upon the two scores s_1 ands$_2$ is better than hypothesis testing based upon a single score s_1 s_2 .If we know the two densities **p (s_1. . . , sn|diff)** and **p ($s_{1,}$ . . . , sn|same)** , the log-likelihood ratio test achieves the highest verification rate for a given false accept rate **H_0:S_1… S_n ~p ($s_{1\ldots}$ sn|diff)**

$$\text{Log}\ \frac{P(s_{1\ldots}\ sn|same)}{P(s_1. . . ,\ sn|diff)} >< 0$$

However, the true densities p (s_1. . . , sn|diff) and p ($s_{1,}$ . . . , sn|same) are unknown, so we need to estimate these densities observing scores computed from query-target pairs in the training data. One way to estimate these densities is to use nonparametric density estimation. In this work, we use parametric density estimation in order to avoid over-fitting and reduce computational complexity. In particular, we model the distribution of **S_i** given **H_0** as a Gaussian random variable with mean $\mathbf{m_{diff,i}}$ and variance $\boldsymbol{\sigma 2_{diff,i}}$, and model $\mathbf{\{ Si \}\ _i{}^n=1}$ given $\mathbf{H_0}$ as independent Gaussian random variables with density is given by

$$\mathbf{P\ (s_1, \ldots,\ sn|diff)=\prod N(Si;\ {}^m{}_{diff,i},\ \sigma 2_{diff,i})}$$

Where $\mathbf{N\ (Si;\ {}^m{}_{diff,i},\ \sigma 2)=(1/\sqrt{2\pi}\ \sigma^2)exp\{-((x-m)^2/2\ \sigma^2)\}}$is the Gaussian density function. The parameters $\mathbf{{}^m{}_{diff,\ i},\ \sigma 2_{diff,\ i}}$ are estimated from the scores of the i^{th} classifier corresponding to no match query-target pairs in the training database. Similarly, we approximate the density of **{Si}** $\mathbf{{}_i{}^n=1}$ **given** $\mathbf{H_1}$ **by** $\prod$N(Si; $\mathbf{{}^m{}_{same,i},\ \sigma 2\ _{same,i}}$) , and the parameters and $\mathbf{{}^m{}_{diff,\ i},\ \sigma 2_{diff,\ i}}$ **and** $\mathbf{{}^m{}_{same,\ i},\ \sigma 2_{same,\ i}}$ are computed from the scores of the classifier corresponding to match query-target pairs in the training database. Now we define the fused score to be the log-likelihood ratio, which is given by

$$\mathbf{S=\log \frac{N\ (Si;\ {}^m{}_{same,i},\ \sigma^2{}_{same,i})}{N\ (Si;\ {}^m{}_{diff,\ i},\ \sigma^2{}_{diff,\ i})}}$$

4. CONCLUSION

In the proposed approach we have through a whole face recognition system**.** The Retinex method and SQI method are used to smoothed images as the estimation of the extrinsic factor. KPCA offers improved analysis of datasets that have nonlinear structure. It is also useful for generalization that can be applied to the domains where nonlinear features are required. We also plan to use the KPCA algorithm on real earth science data. In this proposed work, we used parametric density estimation in order to avoid over-fitting and reduce the computational complexity with preprocessing, feature extraction and classifier and score fusion for uncontrolled illumination variations. The overall process can be viewed as a pipeline consisting of image normalization, feature extraction, and subspace representation, each stage increases resistance to illumination variations and makes the information needed for recognition more manifest. The integrative framework is proposed to verify the face in various lightening conditions.

5. EXPERIMENTAL RESULTS

The proposed work narrates the frame work of the experimental result as we take the gray scale image (0,255) as the original image. Fig 6 shows the Test image which is to be preprocessed. Fig

7 illustrates the preprocessed image 1 Fig.8 shows the image as we stored in the data base. Fig .9 demonstrates the final preprocessed image3.

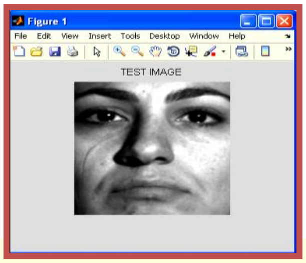

Fig 6: Test Image

Fig 7: Preprocessed Image

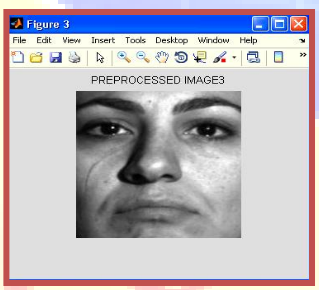

Fig 8: Preprocessed Image 3

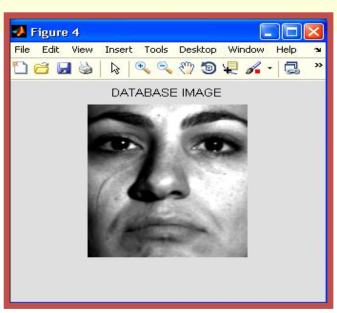

Fig 9: Database Image

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