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A review on Improved Face Recognition using Data Fusion

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Abstract - *The basic concept of this paper is to review on how to use data fusion technique to enhance the performance of the face recognition system. Here we have to study for improvement different fusion approaches. The different fusion approaches consists of like, Feature fusion approach and Decision fusion approach, different data fusion approaches. Feature fusion, here we take over view on the three feature vectors generated using principal component analysis (PCA), discrete cosine transform (DCT) and local binary patterns algorithms (LBP). The feature vector from each extraction technique is then applied to similarity measure classifier. In the decision fusion approach, feature vectors are generated from the three algorithms, which fed to classifiers separately and decisions are combined using majority voting scheme. The proposed strategy was tried utilizing face pictures having diverse outward appearances and conditions got from ORL and FRAV2D information bases as well as camera captured images also.*

Key Words: PCA, LBP, Similarity measurement.

1.INTRODUCTION

Over the most recent twenty years face acknowledgment issue has arisen as a huge exploration zone with numerous potential applications that without a doubt lighten and help protect our regular day to day existences in numerous angles. By and large, face portrayal fizzles into two classes. The First classification is worldwide methodology or appearance- based which utilizes all encompassing surface highlights and is applied to the face or explicit district of it. The second classification is highlight based or part based, which utilizes the mathematical relationship among the facial highlights like mouth, nose, and eyes. Rather than that this paper is introduced to use information combination for enhancing the face recognition. The thought behind this paper is to utilize information combination strategy to improve the presentation of the face acknowledgment framework. Two combination approaches are utilized. Highlight combination approach, were we connected the three element vectors produced utilizing head segment examination, discrete cosine change and nearby twofold examples calculations. The new element vector is at that point applied to closeness measure classifier. In the choice combination approach, include vectors created from the three calculations are taken care of to classifiers independently and choices are intertwined utilizing dominant part casting a ballot approach. Analyses with various situations are executed on two data sets, to be specific; ORL information base and FRAV2D data set.

The paper is concentrated only on Feature fusion technique which combines three feature vectors.

2. LITERATURE REVIEW:

F. Al-Osaimi, M. Bennamoun and A. Mian, —"Spatially Optimized Data Level Fusion of Texture and Shape for Face Recognition". [1] This paper proposes Data-level fusion is believed to have the potential for enhancing human face recognition. However, due to a number of challenges, current techniques have failed to achieve its full potential. Propose spatially optimized data/pixel-level fusion of3-Dshape and texture for face recognition. Fusion functions are objectively optimized to model expression and illumination variations in linear subspaces for invariant face recognition. Parameters of adjacent functions are constrained to smoothly vary for effective numerical regularization. In addition to spatial optimization, multiple nonlinear fusion models are combined to enhance their learning capabilities. Experiments on the FRGC v2 data set show that spatial optimization, higher order fusion functions, and the combination of multiple such functions systematically improve performance, which is, for the first time, higher than score-level fusion in a similar experimental setup.

T. Ahonen, A.Hadid and M.Pietikainen. —"Face Recognition with Local Binary Patterns".[2] this paper take the over view on This paper presents a novel and efficient facial image representation based on local binary pattern (LBP) texture features. The face image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a face descriptor. The performance of the proposed method is assessed in the face recognition problem under different challenges. Other applications and several extensions are also discussed.

Z. M. Hafed and M. D. Levine, -"Face Recognition Using the Discrete Cosine Transform".[3] An accurate and robust face recognition system was developed and tested. This system exploits the feature extraction capabilities of the discrete cosine transform (DCT) and invokes certain normalization techniques that increase its robustness to variations in facial geometry and illumination. The method was tested on a variety of available face databases, including one collected at McGill University. The system was shown to perform very wellwhen compared to other approaches.

V. Perlibakas. —"Distance Measures for PCA-Based Face Recognition". [4] In this article we propose a novel Wavelet Packet Decomposition (WPD)-based modification of the classical Principal Component Analysis (PCA)-based face recognition method. The proposed modification allows using PCA-based face recognition with a large number of training images and performing training much faster than using the traditional PCA-based method. The proposed method was tested with a database containing photography's of 423 persons and achieved82–89% first one recognition rate. These results are close to that achieved by the classical PCA based method (83–90%).

Face Sensing Engine [5] This engine offers face detection, tracking, feature point extraction/tracking.

And also subject identification from images and videos. Their customers include Casio and Nikon.

VeriLook 3.2 algorithm [6] this algorithm is designed for biometric systems. It boosts the following features: multiple face detection, simultaneous multiple face processing, live face detection, face image quality determination, tolerance to face posture, multiple samples of the same face, identification capability, fast face matching, and compact face features template and a features generalization mode. Their customers include Lenova, and several passport and voter control systems. One of the applications which stand outs by making the face detection and recognition work together is iPhoto 09. It provides a very useful and powerful way to organise individual's photo library.

3. PROPOSED METHODOLOGY:

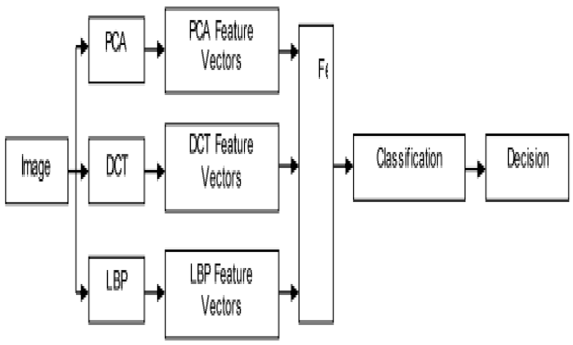
3.1 Feature Extraction:

The Feature extraction is an exceptionally critical phase of information groundwork for later on future handling, for example, identification, assessment and acknowledgment. It is one of the primary explanations behind deciding the strength and the execution of the framework that will use those highlights. It's imperative to pick the component extractors cautiously relying upon the ideal application. As the design regularly contains repetitive data, planning it to a component vector can dispose of this repetition and protect a large portion of the characteristic data substance of the design. The separated highlights have incredible job in recognizing input designs. In this work, utilize highlights got from head part examination (PCA) discrete cosine change (DCT) and nearby parallel examples (LBP) .The thought here was to utilize different calculations to ensure extraction of the most notable highlights out the face pictures. For numerical models of these 3 calculations per users should get back to previously referenced relating references.

3.2 Feature Fusion:

The part vectors eliminated using the extraordinary counts are interwoven to achieve feasibly higher affirmation rates. In this work, we investigated two plans, specifically, interlacing PCA, DCT and LBP incorporate vectors isolated from the face pictures, and interlacing the course of action decisions obtained freely from the three component extractors.

In feature fusion scheme, feature extraction is performed using PCA, DCT and LBP algorithms. The extracted feature vectors from the above algorithms are concatenated to construct a new feature vector to be used for classification as shown in Figure 1.



The feature vectors are extracted using three feature extraction algorithms namely, PCA, DCT and LBP. In feature fusion scheme, a feature vector of face image is formed by concatenating the extracted feature vectors using the previously mentioned algorithms. Assuming F1, F2 and F3 are the feature vectors generated using PCA, DCT and LBP algorithms, respectively. The feature vectors are defined as follows:

$$V_{PCA} = \left[\frac{F_1}{\|F_1\|}\right], \quad (1)$$

$$V_{DCT} = \left[\frac{F_2}{\|F_2\|}\right], \quad (2)$$

$$V_{LBP} = \left[\frac{F_3}{\|F_3\|}\right], \quad (3)$$

$$V_{Fusion} = \frac{[V_{PCA}\ V_{DCT}\ V_{LBP}]}{\|[V_{PCA}\ V_{DCT}\ V_{LBP}]\|}, \quad (4)$$

Where ||.|| is the second norm. Since the ranges of the values ın the feature vectors extracted from the three different algorithms are not same, the feature vectors F1, F2 and F3 are normalized as in (1)-(4), respectively, to make sure that the influence of the three different algorithms to the feature vectors are similarly weighted. Feature Fusion is the final feature vector generated by concatenating the three feature vectors obtained using the three feature extraction algorithms.

3.3 PCA in Face Recognition:

The images of the faces we have are in two dimensions; let us say of size NXN. Our aim here is to find the Principal components (also known as Eigen Faces) which can represent the faces present in the training set in a lower dimensional space.
For all our calculations we need the input data i.e. the faces is a linear form so we map the NXN image into a 1XN2 vector. Let every linear form of the image in our training set be represented by In. Let the total no. of faces in the training set be represented as M.

Steps For Computation of the Principal components*:*

- We compute the mean of all the faces vectors:
- Next we subtract the mean from the image vector Ii.
- We compute the covariance matrix C:

$(N^2XN^2$ matrix)

Where, B = [K1K2 K3 … KM]^T (N^2 X M matrix)

- Our next step is to compute the eigen vector of the matrix C or BB^T, let it be u_i. But BB^T has a very large size and the computation of eigen vector for it is not practically possible. So instead we find the eigen vector for the matrix B^TB, let vi be the eigen vectors.

$B^TBvi = l_iv_i$

- Relationship between v_i and u_i

B^TBv_i = livi

=> BB^TBvi = liAvi

=> CBvi = liBvi

=>Cui =liui where ui = Bvi

- So BB^T and B^TB have same eigen value and there eigen vector are related by ui = Bvi
- The M eigenvalues of BTB (along with their corresponding eigenvectors) correspond to the M largest eigenvalues of BBT (along with their corresponding eigenvectors).
- So now we have the M best eigen vector of C. From that we choose N1 best eigen vectors i.e. with largest eigen value. The N1 eigen vector that we have chosen are used as basis to represent the faces. The eigen vectors should be normalised. The eigen vectors are also referred to as eigen facesbecause when it is transformed into a N X N matrix it appears as "ghostly faces" consisting features of all the training faces.

Representing faces onto this basis:

Each face (minus the mean) Ki in the training set can be represented as a linear combination of N1 eigenvectors:

wj is the projection of Kj on to the eigen vector uj

So each normalized face Ki can be represented in form of the vector,

Recognizing an Unknown Face:

Given an unknown face image (centred and of the same size like the training faces) we follow these steps to recognise it:

• We first convert it to the linear form, I

• Then we normalise it by subtracting the mean from it

K = I –mean

• Next we project K on all the N1 eigen vectors to obtain the vector W

W = [w1 w2 ….. wN1]T

Now, we find

er = minl ||W-Wl||

• So er gives the minimum distance the given face has from another face belonging to the training set. The given face belongs to that person to whom the face in the training set belongs.

• If the value of er is greater than the threshold T1 but less then threshold T2 then we can say that it doesn't belong to any one in the given training set.

If er is greater than threshold T2 we can say that the given image doesn't belong to face space and hence is not the image of a face.

3.4 Basic local Binary pattern (LBP):

LBP concept is applied to area like face recognition, dynamic texture recognition and shape localization. The Local Binary Pattern (LBP) method is widely used in 2D texture analysis. The LBP operator is a non-parametric 3x3 kernel which describes the local spatial structure of an image. It was first introduced by Ojala et al who showed the high discriminative power of this operator for texture classification. At a given pixel position (xc; yc), LBP is defined as an ordered set of binary comparisons of pixel intensities between the Centre pixel and its eight surrounding pixels. The decimal values of the resulting 8-bit word (LBP code) leads to 28 possible combinations, which are called Local Binary Patterns abbreviated as LBP codes with the 8surrounding pixels. The basic LBP operator is a fixed 3x3 neighbourhood.

If the gray value of the center pixel is Ic and the gray values of his neighbors are, with n= 0, ..., n - 1, than the texture T in the local neighborhood of pixel (xc, yc) can be definedas:

$T = t(I_C, I_0, \ldots\ldots I_{n-1})$ (1)

Once these values of the points are obtained is it also possible do describe the texture in another way. This is done by subtracting the value of the center pixel from the values of the points on the circle. On this way the local texture is represented as a joint distribution of thevalue of the center pixel and the differences:

$T = t(I_C, I_0 - I_C, \ldots\ldots I_{n-1} - I_C)$ (2)

Since t(Ic) describes the overall luminance of an image, which is unrelated to the local image texture, it does not provide useful information for texture analysis. Therefore, much of the information about the textural characteristics in the original joint distributions preserved in the joint difference distribution (Ojala et al. 2s001):

$T \cong t(I_0 - I_C, \ldots\ldots I_{n-1} - I_C)$ (3)

Although invariant against gray scale shifts, the differences are affected by scaling. Toachieve invariance with respect to any monotonic transformation of the gray scale, only thesigns of the differences are considered. This means that in the case a point on the circle has ahigher gray value than the center pixel (or the same value), a one is assigned to that point,and else it gets a zero:

$T \cong t(s(I_0 - I_C), \ldots\ldots s(I_{n-1} - I_C))$ (4)

Where,

$S(x) = \{1, \text{if} \ldots x \geq 0\}$

$S(x) = \{0, \text{if} \ldots x < 0\}$

2.5 Similarity Measures:

The similarity measures used in our experiments to evaluate the efficiency of different representation and recognition methods include L1 distance measure, δL1, L2 distance measure, δL2, and cosine similarity measure, δ_{cos}, which are defined as follows

$d_{L1}(x, y) = \Sigma\ |x_n - y_n|,$ (5)

$d_{L2}(x, y) = (x - y)^t (x - y),$ (6)

$d_{cos}(x, y) = -x^t y \,/\, ||x||\ ||y||,$ (7)

In the experiments for face recognition, three similarity measures are used, namely; Manhattan (L1) distance, Euclidean (L2) distance, and Cosine (Cos) distance. Many experiments are implemented as it shown in the following sections. Firstly, we implemented the face recognition system using the three feature algorithms separately without the use of fusion technique using both ORL and FRAV2D databases.

4. CONCLUSION

In this paper we introduce the use of data fusion for improving the face recognition performance. How to apply fusion techniques like, vectors of PCA and LBP for fusion. Experimental results will be show the benefit of using such techniques in the face recognition problem. Both techniques shows promising results but more sophisticated experiments may led us to find out which technique is optimal for face recognition problem. Also, the effect of using combined techniques on system performance can be investigated in the further work.

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