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# Improved Face Recognition using Data Fusion

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***Abstract –****Thebasic concept of this paper is to use data fusion technique to enhance the performance of the face recognition system. Here for improvement two fusion approaches are used. Feature fusion approach and Decision fusion approach. Feature fusion, here we concatenated 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.*
***Keywords****—PCA, LBP, DCT, Similarity measurement.*

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## I. 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.

## II. PROPOSED METHODOLOGY:

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 perusers should get back to previously referenced relating references.

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.

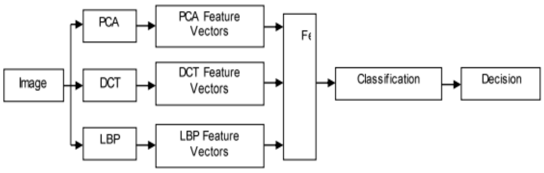


Fig. 1: Block diagram for feature fusion

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:

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

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

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

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

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. PCA in Face Recognition:

The images of the faces we have are in twodimensions; let us say of size NXN.Our aim here is to find the Principal components (also known as Eigen Faces) which canrepresent 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 eigenvalue.The N1 eigen vector that we have chosen are used as basis to represent the faces. Theeigen vectors should be normalised. The eigen vectors are also referred toaseigenfacesbecause 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.

4.Basic local Binary pattern (LBP):
LBP concept is applied to area like face recognition, dynamic texture recognitionandshape localization. The Local Binary Pattern (LBP) method is widely used in 2Dtexture analysis. The LBP operator is a non-parametric 3x3 kernel which describes thelocal spatial structure of an image. It was first introduced by Ojala et al who showed thehigh discriminative power of this operator for texture classification. At a given pixelposition (xc; yc), LBP is defined as an ordered set of binary comparisons of pixelintensities between the Centre pixel and its eight surrounding pixels. The decimal valuesof the resulting 8-bit word (LBP code) leads to 28 possible combinations, which arecalled Local Binary Patterns abbreviated as LBP codes with the 8surrounding pixels.The basic LBPoperator is a fixed 3x3 neighbourhood.
If the gray value of the center pixel is Ic and the gray values of his neighbors are, withn= 0, ..., n - 1, than the texture T in the local neighborhood of pixel (xc, yc) can be
Definedas:

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

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

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

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

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

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 ahighergray value than the center pixel (or the same value), a one is assigned to that point,and else it gets a zero:

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

Where,

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

5. Discrete Cosine Transform (DCT)
A transform is a mathematical operation that when applied to a signal that is being processed converts it into a different domain and then can be again is converted back to the original domain by the use of inverse transform The transforms gives us a set of coefficients from which we can restore the original samples of the signal. Some mathematical transforms have the ability to generatedecorrelated coefficients such that most of the signal energy is concentrating in a reduced number of coefficients.
The Discrete Cosine Transform (DCT) also attempts to decorrelate the image data as other transforms. After decorrelation each transform coefficient can be encoded independently without losing compression efficiency. It expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. The DCT coefficients reflect different frequency component that are present in it. The first coefficient refers to the signal's lowest frequency(DC component) and usually carries the majority of the relevant information from the original signal. The coefficients present at the end refer to the signal's higher frequencies and these generally represent the finer detailed. The rest of the coefficients carry different information levels of the original signal.
Definition:

Ahmed, Natarajan, and Rao (1974) first introduced the discrete cosine transform (DCT) in the early seventies. Ever since, the DCT has become very popular, and several versions have been proposed (Rao and Yip, 1990). The DCT was categorized by Wang (1984) into four slightly different transformations named DCT-I, DCT-II, DCT-III, and DCT-IV. Here we are using only DCT-II and is referred to as DCT and DCT-III as inverse DCT henceforth.

One dimensional DCT transform is defined as :

$0 \leq k \leq N-1$

Where u(n) in the input sequence of length N and its DCT is v(k) and
(0) =
(k) = $1 \leq k \leq N-1$
The inverse discrete cosine transform permits us to obtain u (n) from v (k). It is defined by:

$0 \leq n \leq N-1$

In 2 dimension the DCT is defined as ,

For u, v = 0,1,2,…,N -1 and α(u) and α(v)are defined above.

Its inverse is given by: for x,y = 0,1,2,…,N -1.

6. Similarity Measures:
The similarity measures used in our experiments to evaluate the efficiency ofdifferent representation and recognition methods include L1distance measure, δL1, L2distance measure, δL2, and cosine similarity measure, $\delta_{cos}$, which aredefined as follows
$d_{L1}(x, y) = \Sigma |x_n - y_n|$,(5)
$d_{L2}(x,y) = ( x - y )t ( x-y )$ , (6)
$d_{cos}(x, y) = - xty / ||x|| \, ||y||$ , (7)

In the experiments for face recognition, three similarity measures are used, namely;Manhattan (L1) distance, Euclidean (L2) distance,and Cosine (Cos) distance. Manyexperiments are implemented as it shown in the following sections.Firstly, weimplemented the face recognition system using the three feature algorithms separatelywithout the use of fusion technique using both ORL and FRAV2D databases.

## III. RESULT AND DISCUSSION:

In these experiments we implemented PCA, DCT, and LBP algorithms for face recognition separately. Three similarity measures are used as classifiers. Number of used training images changed between 1 to 9out of 10 images per person. Table 1 and Table 2 show the obtained results using ORL and FRAV2D databases, respectively he 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, δcos, which are defined as follows,

**Table 1:** Experimental results on ORL database using PCA, DCT and LBP separately with different similarity measures

| Algorithm | Similarity Measure | Number of training images | | | | |
|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** |
| **PCA** | **L1** | 61.4108 | 61.4234 | 61.0091 | 61.8519 | 62.5228 |
| | **L2** | 61.3941 | 61.3887 | 61.0081 | 61.8889 | 62.4818 |
| | **Cos** | 61.4387 | 61.4746 | 61.0336 | 61.9493 | 62.5741 |
| **LBP** | **L1** | 54.6478 | 54.4423 | 53.9209 | 54.5019 | 54.2904 |
| | **L2** | 54.6505 | 54.4447 | 53.9222 | 54.5018 | 54.2941 |
| | **Cos** | 54.6438 | 54.4381 | 53.9191 | 54.4953 | 54.2855 |

## IV. CONCLUSION

In this paper we introduce the use of data fusion for improving the face recognition performance. Twofusion techniques were applied, namely; feature fusion using PCA and LBP. Experimental results show thebenefit of using such techniques in the face recognitionproblem. Both techniques shows promising results butmore sophisticated experiments may led us to find outwhich technique is optimal for face recognition problem.Also, the effect of using combined techniques on systemperformance can be investigated in the further work.

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