A Survey on Comparison of Face Recognition Algorithms

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Abstract— **The identification of a face from a video or image source is a study of computer vision know as face detection or recognition. Face detection and recognition becomes popular in recent years by the development of computing power. In this study we will present performance aspect of algorithms Eigenfaces, Fisherfaces, and Local Binary Pattern Histograms in different development platforms: Arm and Intel processors.**

***Index Terms*—Embedded, Face Recognition, Eigenfaces, Fisherface, LBPH.** *(key words)*

I. Introduction

The identification of a face from a video or image source is a study of computer vision know as face detection or recognition. Face detection and recognition becomes popular in recent years by the development of computing power. It has wide range of applications including: biometrics, content-based image retrieval systems, photography and video processing.

Computing and visual sensing technologies in today's world has reach to a state that inexpensive, reliable and accurate solutions can be feasible. Many embedded systems supplied with CMOS camera can be used in face detection systems, and because of the heavy computing process, a developed versions of this systems can be used in face recognition.

One of major application of face recognition system is biometric devices and many studies are going on, a different type of application can be used in segmenting a movie among with its cast. This application can be used in jumping any scene of your favorite actor/actress.

Television or media player are equip with enhanced embedded systems, which can perform face recognition off-line or on-line.

When the job is recognition of a face in a movie, the process becomes more complicated, since the images you have to process are generally not in an ideal condition like in biometric devices. The person you have to detect and recognize can be in various conditions. These conditions can be low illumination, contrast and scene conditions.

This study we will present performance aspect of different algorithms in different development platforms.

II. Methods Used

There are many methods used in face recognition. Each has different features under different conditions like illumination, expression and pose change. Among them, for our purpose which is face detection in video stream, we focused on three major methods and we looked their performance under different development environment to find a good matching and low computing costs.

We tried Eigenfaces, Fisherfaces, and Local Binary Pattern Histograms (LBPH) methods to compare with each other. Both Eigenfaces and Fisherfaces methods are one of the well-known techniques for face recognition. They are known to be very sensitive to pixel level variations such as illumination, facial expression and pose variations. LBP is a relatively new method primarily developed for texture analysis. Compared to Eigenfaces and Fisherfaces methods, we found that LBPH is significantly more robust under illumination and pose variations.

A. Eigenfaces

Eigenfaces is based on Principal Component Analysis (PCA). PCA is used to reduce the dimension of an image matrix. For example if face images are represented in g-dimensional space, PCA uses a linear transform and aims to get an h-dimensional subspace, which answers maximum variance in the g-dimensional space and where h is too small according to g. Mean centered images are calculated by subtracting the normalized training images from the calculated mean image. If W is the matrix of mean centered training images W_i (i = 1, 2, ... L) and L is the number of training images, covariance matrix D is calculated from W as in Equation 1.

$$D = W\,W^T \quad (1)$$

To reduce the size of covariance matrix D, we can use $D = W^TW$ instead. Eigenvectors e_i and eigenvalues λ_i are obtained from covariance matrix.

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$$z_{i=} E^T w_i (i = 1,2, \dots, L) \quad (2)$$

In the Equation 2, z_i represents the new feature vector of the new lower dimensional subspace [1].

There is a negative aspect of this method, that it tries to maximize inter and intra class scattering. Inter class scattering is good for classification while intra class scattering is not. In face recognition, if there is variance of illumination, this increases intra class scattering very high, even classes seems stained, and causes low classification[2].

B. Fisherfaces

Linear Discriminant Analysis (LDA) or Fisherfaces aims to increase inter class differences, not data representation.

$$S_w = \sum_{j=1}^{R} \sum_{i=1}^{M} (x_i^j - \mu_j)(x_i^j - \mu_j)^T \quad (3)$$

$$S_b = \sum_{j=1}^{R} (\mu_j - \mu)(\mu_j - \mu)^T \quad (4)$$

The formulas above are intra class (Equation 3) and inter class (Equation 4) scatter matrices respectively. The indices, j is class and i is image number. μ_j is the mean of class j, and μ is mean of all classes. M_j shows the number images in class j, and R is the number of classes. S_b is maximized while S_w is minimized for the classification to be done [1].

C. Local Binary Patterns (LBP)

Local Binary Patterns (LBP) was first presented by Ojala et al. in [3] to use in texture description. The basic method, labels each pixel with decimal values called LBPs or LBP codes, to describe the local structure around of pixel. As illustrated in Figure 1, value of the center pixel is subtracted from the 8 neighbor pixels' values, if the result is negative the binary value is 0, otherwise 1. The calculation starts from the pixel at the top left corner of the 8-neighborhood and continues in clockwise direction. After calculating with all neighbors, an eight digit binary value is produced. When this binary value is converted to decimal, the LBP code of the pixel is generated, and placed to the coordinates of pixel in matrix [4].

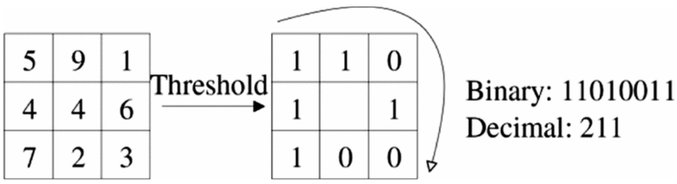

Fig. 1. Basic LBP operator [4]

There is a drawback of LBP which uses 8-neighborhood (3x3) that cannot cover large-scale structures. To take into account texture of different size structures, the method is generalized. In [5] Ojala et al. revised the method to be flexible for any radius and any number of sampling points and named the new method as Extended LBP(ELBP). Figure 2 shows different examples of ELBP operator, and P represents the number of neighbors and R represents the radius of a circle on which neighbors are located.

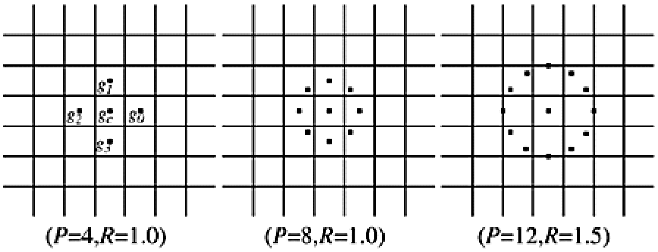

Fig. 2. ELBP operator examples [5]

The histograms of LBP are used for face recognition since LBP histograms contain information about the distribution of local micro patterns. Because the face image is too big for LBP calculation, dividing the image into small regions is proposed in [6]. Some parts of face (like eyes, mouth) contain more information for face recognition. Yang et al. proposes to train and allocate different weights for face parts, by their information covering and then concatenating them end to end to build up global description of face. This helps to collect local pattern information with spatial details of the whole image.

To decide if two face images are belong to same person, the images' histograms are compared. Chi square statistic similarity measure is used for comparison of histograms. It can be defined as follows:

$$X_w^2(S, M) = \sum_{i,j} w_j \frac{(S_{i,j} - M_{i,j})^2}{(S_{i,j} - M_{i,j})} \quad (5)$$

where $i = 0,1,\dots,n\text{-}1$, $j = 0,1,\dots,m\text{-}1$, w_j is the weight for region j, S is target face image histogram and M is the query face image histogram[6].

III. EXPERIMENTS

In our study two experiment setups are used. The faces of the TV series Buffy season 5 episode 2 are extracted and three main characters' faces are used in the experiments. Buffy, Michelle and Nicholas are the characters that are chosen. Nicholas is chosen to add at least one male character to testbed. As for male faces are better suited for face recognition algorithms, and thus give better results.

The aim of the study is comparing the face recognition performances of the selected the three methods. So two different testbed is prepared accordingly.

TABLE I. EXPERIMENT TESTBEDS

Characters	Experiment 1		Experiment 2	
	Train(# of face images)	***Test(# of face images)***	***Train(# of face images)***	***Test(# of face images)***
Buffy	14	739	451	302
Michelle	18	606	375	249
Nicholas	13	192	123	82

The difference between the experiments is that, in experiment 1, one track of a face is chosen as training set and

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the rest as test set. In experiment 2, 60% of the images is chosen as training set and 40% as test set.

OpenCV [7] library is used for image processing within the experiments. Microsoft Visual C++ 2010 Express Edition is used for coding and compiling on windows based system. And for arm-Linux system g++ is used to compile the code.

IV. PLATFORMS

We run same algorithms on different platforms, to show how the algorithms benefit from the hardware and see performance variance. The result will guide anyone, who wants to build an embedded face recognition system.

Two different platforms are used. First platform is Intel based running at 2.7 GHz processor with 4 GB ram, labeled as Intel. Second platform is arm based running at 1 GHz processor 512 MB ram, labeled as Arm.

V. RESULTS

The timing performance of the algorithms are shown in Table 2.

TABLE II. EXPERIMENT TIME DURATIONS

Methods	Experiment 1		Experiment 2	
	Intel (seconds)	*Arm (seconds)*	*Intel (seconds)*	*Arm (seconds)*
Eigenfaces	1.91	30.65	432.08	3600
Fisherfaces	5.96	8.3	549.84	3360
LBPH	55.02	136.52	143.61	907.02

As seen in Tab 2, in experiment 1, Eigenfaces made the best score of all three, especially by far to LBPH. But Fisherfaces also gave good result with 5.96 seconds. But overall LBPH is robust to change in the hardware architecture. Especially in Arm platform, LBPH is made the best results.

TABLE III. EXPERIMENT TRUE/FALSE ANSWERS

Methods	Experiment 1			Experiment 2		
	True	*False*	*Hit Ratio (%)*	*True*	*False*	*Hit Ratio (%)*
Eigenfaces	509	1028	33	586	47	93
Fisherfaces	519	1018	34	540	93	85
LBPH	679	858	44	594	39	94

In experiment 1, one face track is used, this causes a decrease in the success of recognition dramatically to the level of random selection. Selecting only one track causes the train set to be inefficient. But in experiment 2, 60% of the whole images are used, and the training set is selected from all tracks.

VI. CONCLUSION

In the article, Eigenfaces, Fisherfaces, and Local Binary Pattern Histograms (LBPH) methods in face recognition is compared with each other in different hardware environments. Their recognition success and performance are measured.

The results showed that Fisherface gives best timing while lack of successful recognition and LBPH has succeed in recognition with the expense of performance.

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