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Face Recognition Using Eigen-Face Implemented On DSP Processor

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Abstract— This paper focus to develop an automatic face recognition using holistic features extracted that use the global features represented by low frequency data from face image. Holistic features are extracted using Eigen-face method where a linear projection technique such as PCA is used to capture the important information in the image. Euclidean distance is used for matching process. The propose method is tested using a benchmark ORL dataset that has 400 images of 40 persons. Euclidean distance classifier is tested using the TMS320C6713 digital signal processor (DSP). The computational time is less compared with the offline simulation using PC based. The best recognition rate is 95% when tested using 9 training images and 1 testing image represented with 35 PCA coefficients.

Keywords— Holistic features, Eigen-Face, PCA, Euclidean distance, ORL dataset, PCA coefficients, TMS320C6713

INTRODUCTION

Facial biometric is among the fastest growing biometric areas, but building an automated system for human face recognition is a challenge because humans are not well skilled in recognition numerous unknown faces. In recent years, much work has been carried out in face recognition, which has become successful in actual applications [5]. Face recognition can be divided into two main methods: two dimensional (2D) and three dimensional (3D). 2D and 3D refer to the actual dimension in a computer workspace. 2D is "flat", using the horizontal and vertical (X and Y) dimension, the image has only two dimensions. While 3D adds the depth (Z) dimension. This third dimension allows for rotation and visualization from multiple perspectives. Many face recognition methods including their modifications have been developed [3]. Identifying weather, a face is known or unknown can be accomplished by comparing a person's face from a dataset of faces. Research interest in face recognition is rapidly increasing given the many laws and commercial applications of face recognition [8].

Face recognition has special advantages over their system characteristics because it is a non-contact process that can identify a person from a distance. People are not required to place their hands on a reader or their eyes in front of a scanner in a specific position [1]. Face recognition also aids in crime prevention because face images that are recorded and archived can later help identify a person. The advantage of face recognition is not the same based on all kind of methods. Different biometric indicators are appropriate for various kinds of identification applications because of the varying cost, intrusiveness, ease of sensing, and accuracy of these applications [4].

A face recognition classified into verification (one-to-one matting) and identification (one-to-many matching). Face verification will compare the face images against a template face images whose identity is being claimed. Face identification will compare a query face image against all images templates in a face dataset [7]. Figure 1 shows the process of face identification.

Face recognition methods can be divided into the following three categories:

1. Feature-based methods.
2. Appearance-based (Holistic) methods.
3. Hybrid methods.

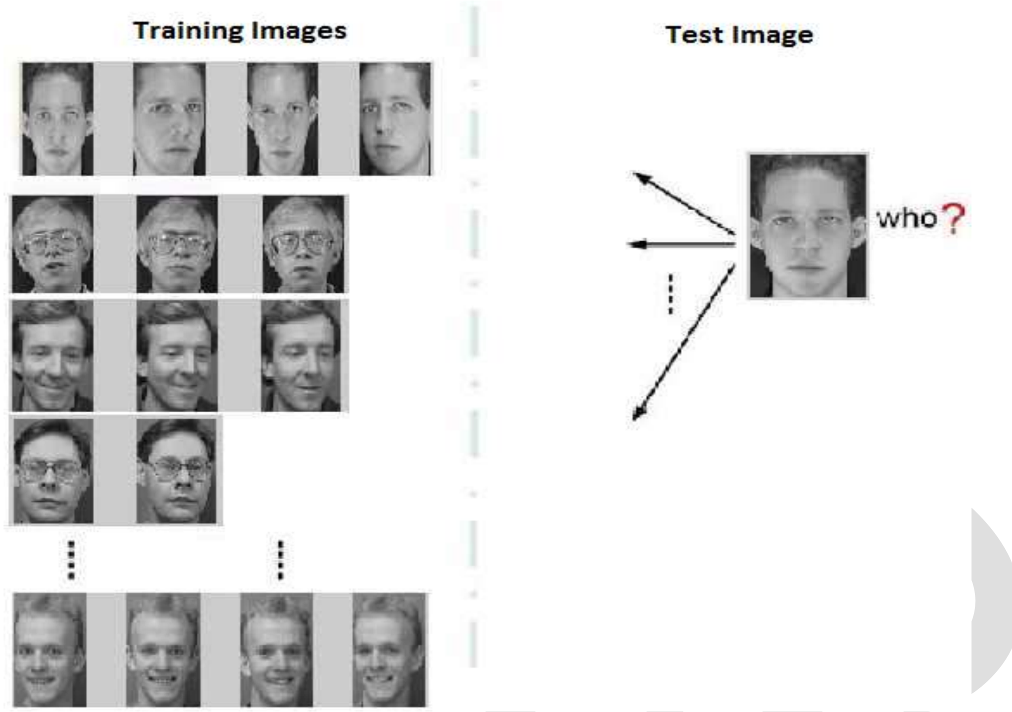

Figure 1: Face Identification Process.

Feature-based methods use a priori information or local facial features to select numerous features and the identify unique individuals. Local features include the eyes, nose, mouth, chin, and head outline, which are selected from face images. Appearance-based methods use global facial information for facial recognition. The features of holistic approaches represent optical variances in the pixel data of face images, which are used to identify one individual from another. Hybrid face recognition system combine both holistic and feature based methods. 3D images are used in hybrid methods [7] [8].

PRINCIPLE COMPONENT ANALYSIS

Numerous face recognition methods have been proposed, motivated by the increasing number of real world applications and by the curiosity on modeling human cognition. One of the most adaptable method for face images results from the statistical method called PCA. PCA is a feature extraction and dimensionality reduction method widely used for image recognition [7].

Covariance eigenvectors must be found to project the image to a lower dimensional feature space. The eigenvector corresponds to the original data directions of the principal components (PCs), and the statistical significance of the eigenvectors is provided by the corresponding eigenvalues. In PCA, the original data image is transformed into a subspace group of PCs [10]. PCA was initially offered by Kirby and Sirovich for face detection and identification. They showed that PCA is an optimal compression scheme the minimizes the mean squared error between original images and image reconstruction for any given compression level.

Applying PCA in face recognition is started by initially performing PCA on a set of training images of known human faces. A group of PCs is then computed from the covariance of the training sample image. Subsequently, the raw data in a high dimensional feature space are projected to a lower feature space through several eigenvectors with the highest eigenvalues. The classification is performed in a low dimensional feature space by using a simple classifier such Euclidean distance [2].

EIGEN-FACE APPROACH

Eigenfaces is a sufficient and efficient method for face recognition because of its learning capability, speed, and simplicity. In biometric recognition systems, the underlying facial information needs to be extracted and encoded efficiently, and one facial encoding is compared with similar information encrypted from the database. Eigenfaces is a projection technique derived from eigenvectors when the raw image is projected to a new basis vector. It is an appearance-based method in face recognition which determines and captures the variation in a collection of face images, and then uses this information to encode and compare the images of human faces holistically. The idea behind extracting such type of information is to capture as many variations as possible from a group of training images [11].

Mathematically, the PCs of the feature distribution of faces can be found using the eigenfaces approach. First, the eigenvectors of the covariance matrix of the group of face images are located, and then the eigenvectors are sorted based on the corresponding eigenvalues [14]. Next, a threshold eigenvalue is determined. Finally, the eigenvectors with the most significant eigenvalue are selected. The original face images are then projected onto the significant eigenvectors to obtain a group called eigenfaces. Every face has a benefaction to the eigenfaces obtained. The perfect eigenfaces from a dimensional subspace is called face space [11].

The test image recognized is also projected onto the face space to obtain a low dimensional feature. Data distribution in the feature space are assumed to the Gaussian. Euclidean distance is used to determine a matching value with all the dataset templates. The matching value of all the training images can be also determined and stored in a distance matrix [2]. The matching value of the test image is then compared with the group of weights of the training images, and the most suitable match is located. The objective function for the decision is to determine the smallest distance value between the test image and the dataset template [12]. Figure 2 show the process of face recognition system.

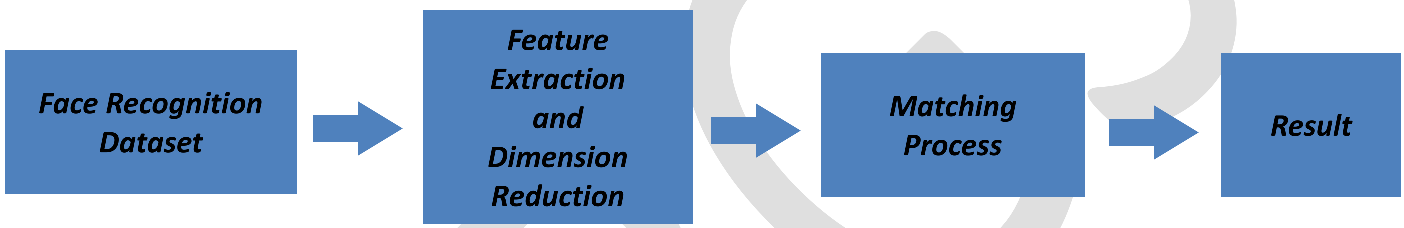

Figure 2: Face Recognition Process.

Training steps are as follows:

Step 1: Acquire an initial set of M number of face images (training images). ORL database with 400 images is used.

Step 2: More than one image I(1), I(2), I(3), ..., I(M) from M number is obtained, where each image has w x h. The image is converted into a single vector and can be represented by the column vector of size w x h. All images are represented as a column vector in this work as shown in Figure 3.

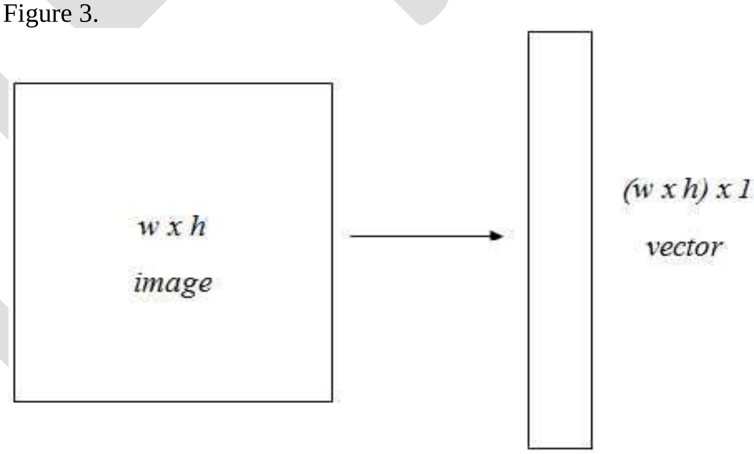

Figure 3: Image Representation.

Step 3: After the images are presented as column vector, the average of the M number of training images is given as follows:

$$av = \frac{1}{M}\sum_{n=1}^{M} I(n) \tag{1}$$

Where M is the total number of the training images.

Step 4: The original vector image is subtracted from the average image computed in the previous step. This process produces zero mean images and can be computed as follows:

$$A = I - av \tag{2}$$

Step 5: The total scatter matrix or covariance matrix is calculated from A, as shown in the equation below:

$$Covar = \frac{1}{M}\sum_{n=1}^{M} A(n)\, A^T(n) = A * A^T \tag{3}$$

Step 6: The eigenvalue and eigenvector of the covariance matrix need to be calculated.

Step 7: The diagonal of the eigenvalue matrix is sorted in decreasing order. The index of each sorted diagonal eigenvalue is sorted in a vector.

Step 8: The principle components is selected by calculating the eigenfaces from the training images. The M highest eigenvalue the belongs to a group of eigenvectors is chosen. These M eigenvectors describe the eigenfaces. Given that new faces are encountered, the eigenfaces can be updated or recalculated accordingly.

Step 9: The corresponding distribution in the M dimensional weight space is calculated for every known person by projecting the person's face image onto the face space.

Step 10: Each training sample is projected onto the eigenfaces space, and the projected features are obtained.

Step 11: When it is close, the weight patterns are classified as either a known person or an unknown person based on the Euclidean distance measured. When it is close enough, the recognition is then regarded as successful, and useful information about the recognized face is provided from the database that contain the face details. The Euclidean distance can be calculated from the equation below:

$$d(X,Y) = \sqrt{\sum_{i=1}^{N}(X_i + Y_i)} \tag{4}$$

Projection the test images are as follows:

Based on the procedure presented in the training phase, the testing phase projects the test image using the eigenvectors developed in the training phase. The testing sample is normalized and then the sample is projected onto the eigenfaces space. The projected test image is compared with the template stored in the dataset to determine the matching values. The training image that produces a minimum distance is assigned to a specific class or group.

Hardware Implementation

The goal of hardware implementation is to develop a prototype DSP platform. The purpose is to identify the individual or multiple faces and archive an acceptable recognition rate with less processing time [6].

In this experiment TMS320C6000 is used because its high performance and suitable for this types of problems. There are three distinct instruction set architectures as listed below:

1. High Performance TMS320C6000 DSP Platform.
2. Control Optimized TMS320C2000 DSP Platform.
3. Power Efficient TMS320C5000 DSP Platform.

TMS320C6713 DSP PROCESSOR

The C6713 DSK is a low cost standalone development platform that enables users to evaluate and develop applications for the TI C67xx DSP family [9]. The DSK comes with a full component of on-board drives that suit a wide variety of application environment Key features are listed in Table 1.

Table 1: TMS320C6713 Key Features.

#	TMS320C6713
1	Operating at 225 MHz
2	16 Mbytes of synchronous DRAM
3	512 Kbytes of non-volatile flash memory
4	4 user accessible LED's and DIP switches
5	Software board configuration through registers implemented in CPLD
6	JTAG emulation through on-board JTAG emulator with USB host interface or external emulator
7	Single voltage power supply (+5v)

RESULT AND DISCUSSION

In this experiment, the ORL dataset is used to validate the proposed method. The images are organized in 40 directories (one for each subject), which have names in the *sn* form, where *n* indicates the subject number between 1 and 40. In each directory there are 10 different images of a person, whose name is in the form of *m.pgm.* where *m* is the image number between 1 and 10 for that person with each images 92 pixels x 112 pixels in size for a total of 10.304 pixels. The subjects comprise 4 females and 36 males. All the images are captured against a dark homogeneous background with the persons in an upright, frontal position, and with some allowance for side movement. Some variations occur in the facial expressions such as smiling/not smiling, open/closed eyes, and other facial details.

1. Analysis with different number of PCA Coefficient

In this analysis, the performance of their recognition system when using different number of PCA coefficient is tested. The number of eigenvectors is increased from 5 to 40, and the best recognition rates are examined in details. When the number of eigenvectors increases, many pieces of information are used during the classification. However, using too many eigenvectors produces less discriminative features because of the noise and redundant information in the feature space. Figure 4 shows the system performance by using different PCA coefficients on five training and five testing images. This analysis show that using 35 PCA coefficient produces results.

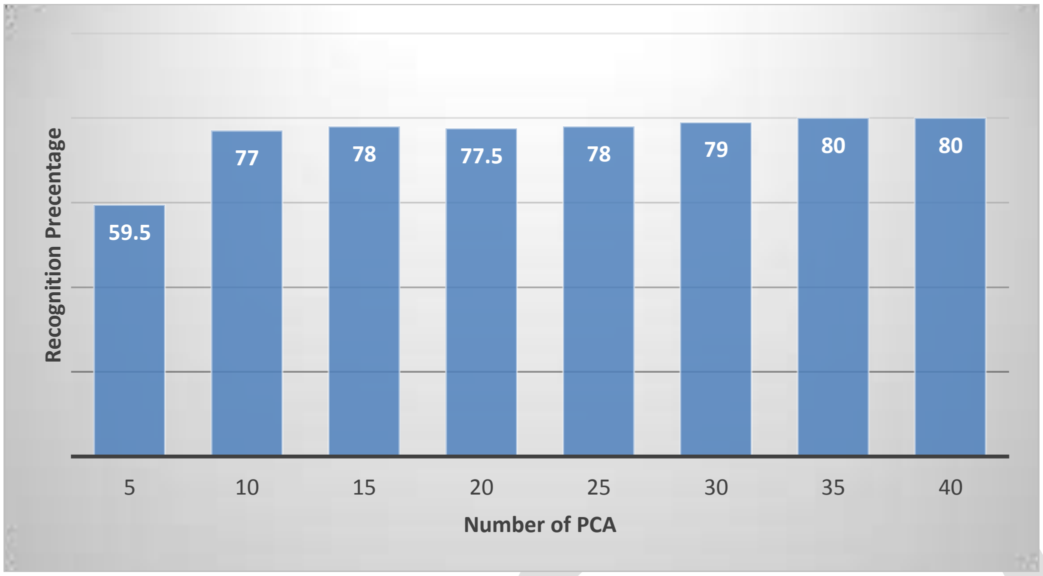

Figure 4: System Performance by Using Different PCA Coefficients

2. Analysis with different number of training and testing images

In this analysis, different number of training and tested images are used to examine the recognition rate. Table 2 shows that increasing the number of training images will increase the recognition rate.

Table 2: Recognition Rate Using Different Number of training and testing images.

No. of Testing Images	No. of Training Images	Recognition Rate
9	1	62.22 %
8	2	71.25 %
7	3	72.86 %
6	4	77.92 %
5	5	80 %
4	6	91.25 %
3	7	93.33 %
2	8	95 %
1	9	95 %

3. Comparison of Euclidean Distance Processing Time Using TMS320C6713 DSP Processor

In this analysis, the effectiveness of the Euclidean distance classifier when implemented using the TMS320C8713 digital signal processor (DSP) is tested. The computational time of the classification process is only examined because implementing the whole system in this board requires a large memory space for data storage. The TMS320 DSP family offers the most extensive selection of DSPs available in the market, with a balance of general purpose and application-specific processors to suit application needs. This processor has a floating point arithmetic logic unit, thus producing efficient computation accuracy. The output interface element, will communicate the decision of the face recognition system to the interfaced asset to enable access to the user. This can be a simple serial communication protocol like RS232, or a higher bandwidth USB protocol. It could also be the TCP/IP protocol via a wired medium. Classification using the TMS320 produces the same recognition rates, but with less processing time, as shown in Table 3. In this analysis, C language program is compiled and build, the PCA coefficient for the template and test image are pre-calculated and are located into the memory module on the DSP board.

Table 3: Processing Time Using TMS320 Compared with PC Based System.

Device	Time Required
PC Based System	5 Second
TMS320 DSP Processor	0.5 Second

CONCLUSION

Face recognition is a challenge because faces can change substantially in term of facial expression, detection, lighting and scale. This paper mainly focuses on the holistic face recognition method. The performance of the statistical PCA method is also investigated. PCA is used for the feature extraction and dimension reduction of given face images, whereas Euclidean distance is used for the matching process. The analysis using the ORL shows the significant performance achieved by this method, which has a 95% recognition rate. Using TMS320C6713 DSP Processor will reduce the time required for recognition process.

REFERENCES:

[1] Singh, Prabhjot, and Anjana Sharma. "Face Recognition Using Principal Component Analysis in MATLAB." (2015).

[2] Kadam, Kiran D. "Face Recognition using Principal Component Analysis with DCT." International Journal of Engineering Research and General Science, ISSN: 2091-2730 (2014).

[3] Gawande, Mohit P., and Dhiraj G. Agrawal. "Face recognition using PCA and different distance classifiers." e-ISSN: 2278-2834,p- ISSN: 2278-8735. (2014).

[4] Fan, ShaSha, Yang Du, Jia Zhao, Qiang Wang, and Fei Guo. "Comparative Research of PCA+ AdaBoost and PCA+ LDA for Face Recognition Technology." In 2015 International Industrial Informatics and Computer Engineering Conference. Atlantis Press, 2015.

[5] Vig, Rekha. "A Gaussian Feature Adaptive Integrated PCA-ICA Approach for Facial Recognition." (2015).

[6] Kumar, Neeraj, Sushree Mahapatro, and Sukanti Pal. "Implementation of Color Image Enhancement using DCT on TMS320C6713." ISSN -2277-1956

[7] Shah, Deepali H., Dr JS Shah, and Dr Tejas V. Shah. "The Exploration of Face Recognition Techniques." International Journal of Application or Innovation in Engg. And Management (IJAIEM) Web Site: www. ijaiem. org Email: editor@ ijaiem. org, editorijaiem@ gmail. com 3, no. 2 (2014).

[8] Parmar, Divyarajsinh N., and Brijesh B. Mehta. "Face Recognition Methods & Applications." arXiv preprint arXiv:1403.0485 (2013).

[9] Kumar, Mr P. Vijaya, and B. Swetha Reddy. "DSP Implementation of Gesture Recognition." (2010).

[10] Abdullah, Manal, Majda Wazzan, and Sahar Bo-Saeed. "Optimizing Face Recognition Using PCA." arXiv preprint arXiv:1206.1515 (2012).

[11] Slavković, Marijeta, and Dubravka Jevtić. "Face recognition using eigenface approach." Serbian Journal of Electrical Engineering 9, no. 1 (2012): 121-130.