Abstract—Nowadays, biometric recognition systems become very popular in security applications. There are many biometric features which can be used for this purpose, such as iris, fingerprints, face, etc. Ear is also a biometric feature. Because of its advantages, many scientists tend to work on this, as well. So in this paper, an embedded ear recognition system is introduced. System is based on an ARM microcontroller which can be programmed with MicroC programming language. Presented recognition system can be used independent from a personal computer, and stored all the dataset in its own memory and experimental results show that, recognition rate is very well.

Keywords—Ear recognition, Principal component analysis, Discriminative Common Vectors Approach, Embedded System.

I. INTRODUCTION

Personal identification for security and different sectors is more important in recent years. The most successful biometric based identification technologies such as iris, fingerprints and face recognition are used in both criminal investigations and high security facilities. These technologies are well studied, but researches show they have many drawbacks which decrease the success of the methods applied [1-4]. Ear biometric is one of the biometrics that changes the least. Ear images are not affected by emotional expression, illumination, aging, pose, and alike. Because of its static structure, easy collection of the data, and the small dimension of the ear image, ear biometric is well suited for long term identification [5-11].

The ear was proposed as a biometric by Burge and Burger in 1998. They proved that ear has a similar performance like face in personal identification tasks [10]. After that some classification techniques such as PCA, LDA, FLDA, etc. applied to ear images for human identification and these papers showed that ear has good performance as a biometric [5-9].

Most realizations of ear recognition were based on personal computers because of strong abilities e.g. high speed for computation, advantage of storage, etc. [2]. Where as in this paper an embedded recognition system based on ear is presented. So, system can be used independent from a personal computer and stored all the dataset in its own memory. In proposed system, algorithms are applied on an ARM Cortex M4 microcontroller. In this microcontroller a new programming language called MicroC is used. Principal Component Analysis (PCA) for dimensionality reduction and Discriminative Common Vectors Approach (DCVA) are applied to the recognition system.

Following sections of this paper will describe these topics in details: In Chapter II principals of the methods are represented. Chapter III mentions about the system specifications and the microcontroller in detail. Chapter IV describes the application. Conclusion is covered in Chapter V.

II. PRINCIPALS OF THE METHODS

A. Principal Component Analysis (PCA)

PCA depends on eigenvector method designed to model linear variations in high dimensional data. PCA performs dimensionality reduction by projecting the original n-dimensional data on to k-dimensional (k<<n) linear subspace. Here, k is the number of the eigenvectors of the data’s covariance matrix. PCA tries to find a set of orthogonal basis functions that capture the directions of maximum variance in data, such that,

$$ J_{PCA}(W_{opt}) = \arg\max_{W} \left| W^{T} S_{T} W \right| $$

is maximized. Here, $S_{T}$ is the total scatter matrix of the training set samples. W is the matrix whose columns are the orthonormal projection vectors [12].

B. Discriminative Common Vectors Approach

DCVA is proposed to extract the common vectors of the classes in a training set by eliminating the differences of the samples in each class. A common vector for each individual class is obtained by removing all the features that are in the direction of the eigenvectors corresponding to the nonzero eigenvalues of the scatter matrix of its own class. In this case, a better criterion is given below
\[ J_{\text{DCVA}}(W_{opt}) = \arg \max_n \left| W^T S_n W \right| = \arg \max_n \left| W^T S_n W \right| \]

\[ = \arg \max_n \left| W^T S_{\text{com}} W \right| \quad (2) \]

Here, \( S_B \) is the between-class scatter matrix, \( S_W \) is the within-class scatter matrix, and \( S_{\text{com}} \) is the scatter matrix of the common vectors \([13-17]\).

In this sense, since all the scatter matrices are known, it is necessary to find the nonzero eigenvalues and corresponding eigenvectors of \( S_n \). In here, there will be at most \( M - K \) eigenvectors. Considering \( Q = [q_1, q_2, \ldots, q_K] \) as a matrix consists of eigenvectors which are determined from \( S_n \). After that, with any chosen sample from each class, common vectors can be computed. One can obtain the common vectors as follows.

\[ x^m_k = x^m_k - Q Q^T x^m_k \quad k = 1, \ldots, N; \quad m = 1, \ldots, K \quad (3) \]

Equation (3) results with a new matrix of common vectors of all classes. Later, it is necessary to find the scatter matrix of common vectors as follows.

\[ S_{\text{com}} = \sum_{m=1}^{K} (x^m_{\text{com}} - \mu_{\text{com}})(x^m_{\text{com}} - \mu_{\text{com}})^T \quad (4) \]

where

\[ \mu_{\text{com}} = \frac{1}{K} \sum_{m=1}^{K} x^m_{\text{com}} \quad (5) \]

denotes the mean of all common vectors.

Then, same eigenvector computation should be applied to \( S_{\text{com}} \). This computation will lead to at most \( K - 1 \) eigenvectors. Considering these eigenvectors as \( w = [w_1, w_2, \ldots, w_{K-1}] \) These eigenvectors will be used to determine the feature vectors using.

\[ \delta^m_k = w^T x^m_k \quad k = 1, \ldots, N; \quad m = 1, \ldots, K \quad (6) \]

These feature vectors are called as discriminative common vectors. Determining the feature vectors, DCVA process ends. This processes is applied to an embedded ear recognition system.

**C. Jacobi Iteration Method**

Jacobi iteration is a powerful algorithm to find eigenvalues and eigenvectors for a symmetric matrix. It computes uniformly accurate answers for the results. \([18-25]\). It is proper to find eigenpairs as a numeric solution for embedded system.

It is supposed that \( A \) is a vector in \( d \)-dimensional space and \( B \) is linear transformation matrix of \( A \), so \( B = RA \), where \( R \) is an \( d \times d \) matrix.

Rotation matrix \( R \) is the same as the identity matrix except four value in the center. So,

\[ b_i = a_i \text{ when } i \neq m \text{ and } i \neq n \quad (8) \]

others,

\[ b_m = a_m \cos \theta + a_n \sin \theta \quad (9) \]

\[ b_n = -a_m \sin \theta + a_n \cos \theta \quad (10) \]

Eigenvalue is

\[ AV = \lambda V \quad (11) \]

\( \lambda \) is eigenvalue of matrix \( A \) and \( V \) is eigenvector of matrix \( A \) related with \( \lambda \). It is supposed that \( P \) is non-singular matrix and that \( B \) is defined by

\[ B = P^{-1} AP \quad (12) \]

It is multiplied both terms of (12) on the right side by \( P^{-1} \). This yields

\[ B P^{-1} V = P^{-1} A P V = P^{-1} A V \quad (13) \]
\[ BP^{-1}V = P^{-1}\lambda V = \lambda P^{-1}V \quad (14) \]

If the variable transform is applied

\[ Z = P^{-1}V \quad (15) \]

So,

\[ BZ = \lambda Z \quad (16) \]

\( Z \) is eigenvector of matrix \( B \). Consequently it is observed that \( A \) and \( B \) is the similarity matrices that is not changing the eigenvalue \( \lambda \) but there is a same connection between \( A \) and \( B \) matrices eigenvectors like in the (15).

It is supposed that \( R \) is used as an orthogonal matrix \((R^T=R^{-1})\) instead of matrix \( P \) and likewise \( D \) is an diagonal matrix for matrix \( B \). This produces,

\[ D = R^{-1}AR = R^TAR \quad (17) \]

When the same procedure is done, eigenvalues of matrix \( A \) is occurred in the diagonal of matrix \( D \). It is formed the sequence of orthogonal matrices \( R_1, R_2, \ldots, R_n \) as follows:

\[ D_1 = A \quad \text{and} \quad D_i = R_i^T D_{i-1} R_i \quad \text{for} \quad i = 1, 2, \ldots \quad (18) \]

When loop converges to infinite, it will be formed eigenvalues of matrix \( A \), but the time is important for embedded system.

\[ \lim_{i \to \infty} D_i = D = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_n) \quad (19) \]

When the off-diagonal elements are close to zero or threshold value, loop will be stopped. Then, it will be obtained

\[ D_n = R_n^T R_{n-1}^T \ldots R_1^T A R_1 \ldots R_{n-1} R_n \quad (20) \]

If it is shorten

\[ R = R_1 R_2 \ldots R_{n-1} R_n \quad (21) \]

Then,

\[ AR = RD = R \text{ diag}(\lambda_1, \lambda_2, \ldots, \lambda_n) \quad (22) \]

Eigenvalues of matrix \( A \) are replaced on the diagonal of matrix \( D \). Initially, it is supposed that \( V \) is identity matrix. Then, eigenvectors of matrix \( A \) is calculated for each loop,

\[ V = VR_1 R_2 \ldots R_{n-1} R_n \quad (23) \]

Matrix \( V \) indicates eigenvectors of matrix \( A \) in the last loop.

It is needed a threshold value \( \varepsilon \) for stopping the loop. The average size of diagonal element can be calculated in every loop,

\[ K = \frac{\sum_{i=1}^{n} |\alpha_i|^2}{n} \quad (24) \]

\[ |a_{mn}| > \varepsilon \left( \frac{K}{a} \right)^{1/2} \quad (25) \]

The magnitudes of the off-diagonal elements are compared to \( \varepsilon (Kn)^{1/2} \).

III. SYSTEM DESCRIPTION

A. Micromedia for STM32 M4

In this paper, an embedded ear recognition system is realized on a compact microcontroller card which is called STM32 M4 shown in Fig.1. It is a development card with lots of peripherals which can allow the development of devices with multimedia contents. The main part of the microcontroller card is 32-bit ARM Cortex-M4 based on STM32F407VGT6. It has a 320x240 TFT touch screen display, 168MHz clock speed, 192KB SDRAM memory and 1 MB ROM memory.

![Fig. 1. Mikromedia for STM32 M4](image)

In this work, training and test sets are stored in 1MB ROM. Neither external flash memory nor MMC card is used in the proposed system. This is an advantage of our system.
In ear database which was used in the system, contains both left and right ear images of 50 individuals. There are 12 images from each individual, 6 from left ear and 6 from right ear. Images were taken at 0 to 15 degrees rotation under the same lighting condition. This ear database is called MIDAS’ EAR Database [7]. Left and right ear images of a person are shown in Fig.2.

Previous recognition systems and proposed ear recognition system are compared shown in Table I.

**TABLE I. COMPARISON OF PREVIOUS WORKS**

<table>
<thead>
<tr>
<th>Year</th>
<th>System</th>
<th>CPU</th>
<th>Memory</th>
<th>Number of Examples</th>
<th>Dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005 [4]</td>
<td>Pentium IV PC</td>
<td>1.7 GHz</td>
<td>-</td>
<td>Video</td>
<td>320x240</td>
</tr>
<tr>
<td>2009 [1]</td>
<td>ARM920T-PXA270</td>
<td>624 MHz</td>
<td>64 MB</td>
<td>-</td>
<td>32x32</td>
</tr>
<tr>
<td>2010 [3]</td>
<td>Magic ARM2410 + LINUX</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2010 [2]</td>
<td>XScale DMA-270 + LINUX</td>
<td>520 MHz</td>
<td>64 MB SDRAM + 32 MB NOR Flash</td>
<td>8 users, 50 Testing Images</td>
<td>40x40</td>
</tr>
<tr>
<td>2013 (Our Work)</td>
<td>STM32 ARM Cortex M4</td>
<td>168 MHz</td>
<td>192 KB SDRAM + 1 MB ROM Memory</td>
<td>20 Classes, 5 samples per class + 50 Test Image</td>
<td>80x60</td>
</tr>
</tbody>
</table>

Proposed system stores two kind of sets. one is training set and the other one is test set.

**B. Training Set**

In this system, training set is composed of 20 subjects. Each subject has 5 images and totally 100 images. For image processing procedure, these 100 pictures were converted into gray level images and also dimensions were reduced to 80x60 pixels. And after that each images were saved as a “raw” format picture file. Next, those 100 raw images were saved in the 1MB ROM. This process uses 50% of the ROM approximately.

**C. Test Set**

In this system, test set is composed of totally 50 pictures. First group has 20 pictures. Since the database has 6 images per subject, the remaining 1 picture is chosen as a test picture. Second group consists of 20 pictures, too. Images in this group were chosen arbitrarily from the remaining 30 individuals. And the last group has 10 pictures. These are composed of different images such as flowers, animals, views, etc. This 50 images were recorded to the 1MB ROM too after the same process. This 50 images require 25% of the ROM approximately.

**IV. APPLICATION OF THE SYSTEM**

In the application of DCVA, within scatter matrix for all K classes were computed. The storage restriction makes it hard to calculate all the information. So in order to find the best results for this system, dimensionality reduction was held with PCA algorithm. For this purpose, eigenpairs should be obtained, but this is a hard process especially on a embedded system. In order to determine the eigenpairs, Jacobi iteration numerical method is used and the dimension reduced to 99 eigenvectors.

After the dimensionality reduction, new within scatter matrix S_w can be determined. This new within scatter matrix covers the information of all the samples with 99 eigenvectors now. After that, it is necessary to obtain the projection of the examples on to the null space of new S_w. Practically, because of the high dimension, this is not possible.

Eigenvalues corresponding nonzero eigenvalues of S_w span the range space of S_w. So, by finding those eigenvectors, it can be possible to project the samples on to the null space. These eigenvectors were found with Jacobi iteration numerical method too. In here, it produces totally 80 eigenvectors. This makes it possible to find the common vectors.

Later, it is easy to obtain the scatter matrix of common vectors. S_com can be computed as (4). There would be an eigenvalue, eigenvector problem for this common scatter matrix, again. Since the dimension would be high, duality property was used for S_com as well. And now S_com becomes a K by K dimensional, symmetric matrix. Jacobi iteration was used for this problem once again. This time, there will be at most K – 1 = 19 eigenvectors corresponding to the nonzero eigenvalues. These 19 eigenvectors are called as optimal projection vectors [13-17].

Optimal projection vectors will be helpful to determine feature vectors \( \delta_m \). It is a surprising result that these discriminative common vectors are independent from sample number in each class. This means, it does not matter which sample you choose to find the common vectors. In other words, these discriminative common vectors guarantees the recognition in the samples in the training set [13-17].

In order to recognize the test image, feature vector of it should be obtained, too. So test feature vector is found as follows.
\[ \delta_{\text{test}} = w^T x_{\text{test}} \]  

This feature vector will be compared with the discriminative common vectors for each class using the Euclidean distance.

Since only one vector is compared with the test feature vector, it is an efficient algorithm to apply in embedded real time system. Recognition rates for this algorithm in the system can be reached to 100%.

First, applications about training and test set which shown in Table II is obtained in MATLAB. The best result has achieved with 5 samples. In this example, it is shown in Fig. 3 closeness of ear space and ear class space for each of test pictures. Ear space and ear class space in 1500 and 415 were used as threshold values respectively. Then, same example with jacobi iteration is realized in MATLAB and embedded system.

Norm error for euclidean distance is formed with reference to the original functions of MATLAB. When Jacobi iteration coefficient increases, norm error decreases both of systems. From Table III and Table IV, norm error for jacobi algorithm is approximately same. This situation also shows that the application is done correctly. Although the execution time takes a long time for training set, it takes very short time for test set. Thus, this system can be used for real-time applications.

TABLE II. APPLICATIONS ABOUT TRAINING AND TEST SET FOR MATLAB

<table>
<thead>
<tr>
<th>Class number</th>
<th>Sample number</th>
<th>Total of ear pictures</th>
<th>Number of ear picture of authorized people</th>
<th>Ear picture of unauthorized people</th>
<th>Number of non-ear pictures</th>
<th>Total number of pictures</th>
<th>Threshold of ear class</th>
<th>Threshold of ear space</th>
<th>Rate of recognition %</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>5</td>
<td>100</td>
<td>20</td>
<td>30</td>
<td>10</td>
<td>60</td>
<td>415</td>
<td>1500</td>
<td>100</td>
</tr>
<tr>
<td>20</td>
<td>4</td>
<td>80</td>
<td>40</td>
<td>60</td>
<td>20</td>
<td>120</td>
<td>540</td>
<td>1500</td>
<td>95.8</td>
</tr>
<tr>
<td>20</td>
<td>3</td>
<td>60</td>
<td>60</td>
<td>90</td>
<td>30</td>
<td>180</td>
<td>630</td>
<td>1500</td>
<td>90.6</td>
</tr>
<tr>
<td>20</td>
<td>2</td>
<td>40</td>
<td>80</td>
<td>120</td>
<td>40</td>
<td>250</td>
<td>760</td>
<td>1800</td>
<td>88.3</td>
</tr>
</tbody>
</table>

Fig. 3 Result of 50 test pictures for MATLAB (20 ear pictures of authorized people – 20 ear pictures of unauthorized people – 10 non-ear pictures)
Fig. 4: Enlarged representation of 20 ear pictures of authorized people and 20 ear pictures of unauthorized people.

**TABLE III. JACOBI ITERATION SOLUTION FOR MATLAB**

<table>
<thead>
<tr>
<th>ε iteration coefficient</th>
<th>1 100x100 matrix</th>
<th>2 99x99 matrix</th>
<th>3 20x20 matrix</th>
<th>Total Iteration</th>
<th>% Norm error for Euclidean distance</th>
<th>Time of Training</th>
<th>Time of Test</th>
<th>Rate of Recognition %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1e-3</td>
<td>3825</td>
<td>5365</td>
<td>370</td>
<td>9560</td>
<td>4.1420</td>
<td>3.850793 s</td>
<td>less than 1 s</td>
<td>100</td>
</tr>
<tr>
<td>1e-4</td>
<td>7828</td>
<td>7700</td>
<td>455</td>
<td>15983</td>
<td>0.3938</td>
<td>5.051885 s</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>1e-5</td>
<td>11556</td>
<td>9754</td>
<td>519</td>
<td>21829</td>
<td>0.0226</td>
<td>5.801002 s</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>1e-6</td>
<td>13801</td>
<td>11268</td>
<td>571</td>
<td>25640</td>
<td>0.0023</td>
<td>7.541637 s</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

**TABLE IV. JACOBI ITERATION SOLUTION FOR EMBEDDED SYSTEM**

<table>
<thead>
<tr>
<th>ε iteration coefficient</th>
<th>1 100x100 matrix</th>
<th>2 99x99 matrix</th>
<th>3 20x20 matrix</th>
<th>Total Iteration</th>
<th>% Norm error for Euclidean distance</th>
<th>Time of Training</th>
<th>Time of Test</th>
<th>Rate of Recognition %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1e-3</td>
<td>3811</td>
<td>5465</td>
<td>364</td>
<td>9640</td>
<td>4.390319</td>
<td>6 min 29 s</td>
<td>less than 1 s</td>
<td>100</td>
</tr>
<tr>
<td>1e-4</td>
<td>7836</td>
<td>7738</td>
<td>452</td>
<td>16026</td>
<td>0.318988</td>
<td>7 min 10 s</td>
<td>100</td>
<td></td>
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<tr>
<td>1e-5</td>
<td>11664</td>
<td>9688</td>
<td>517</td>
<td>21869</td>
<td>0.2301384</td>
<td>7 min 52 s</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>1e-6</td>
<td>13890</td>
<td>11312</td>
<td>578</td>
<td>25780</td>
<td>0.007423323</td>
<td>8 min 28 s</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>
V. CONCLUSION

In this paper, an embedded ear recognition system is proposed. System is based on STM32F4 Cortex-M4 microcontroller which is independent from a PC or an operating system. System is programmed with MicroC programming language which is similar to C or C++. DCVA has applied to the system for classification but before that for dimensionality reduction PCA has been applied too. During the realization of the system, many numerical methods have been used. System can store the dataset in its memory and this is the main advantage of it. This shows such an embedded recognition systems can be available with very small and cheaper products, as well. According to the experimental results, it does not take long processing time to finish all the processes.

Experimental results show that, this system can be used effectively as an embedded ear recognition system and the recognition rate is very good.

REFERENCES


