Ear Recognition by using Neural Networks

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Abstract: Using ears in identifying people has been interesting at least 100 years. The researches still discuss if the ears are unique or unique enough to be used as biometrics. Ear shape applications are not commonly used, yet, but the area is interesting especially in crime investigation. In this paper, the basics of using ear as biometric for person identification and authentication are presented. In addition, the error rate and application scenarios of ear biometrics are introduced. A set of 17 people has been used for experiments having six or more images each. The data used are given by National Institute of Standards and Technology (NIST). The correct recognition rate is ranging between 84.3% and 91.2% for artificial neural network matching. It depends on neural network training parameters .

Keywords: Biometrics, Ear Recognition, Neural Networks, Fast Normalized Cross Correlation, Training Parameters

1. Introduction

Using ears in identifying people has been interesting at least 100 years. The researches still discuss if the ears are unique or unique enough to be used as biometrics. Ear shape applications are not commonly used, yet, but the area is interesting especially in crime investigation. In chapter I present the basics of using ear as biometric for person identification and authentication. Also the error rate and application scenarios of ear biometrics are presented [16].

1.1 What is biometrics?

A biometric is any human feature that can be measured and used for automated or semi-automated identification. Common examples are fingerprints, iris patterns, and facial patterns; less well-known biometrics include ear geometry, body odour (smell) and gait (the body movement while walking) [16].

In different organizations like financial services, e-commerce, telecommunication, government, traffic, health care the security issues are more and more important. It is important to verify that people are allowed to pass some points or use some resources. The security issues are arisen quickly after some crude abuses. For these reason, organizations are interested in taking automated identity authentication systems, which will improve customer satisfaction and operating efficiency.

The authentication systems will also save costs and be more accurate that a human being. [5] Basically there are three different methods for verifying identity:

(i) possessions, like cards, badges, keys;

(ii) knowledge, like userid, password, Personal Identification Number

(iii) biometrics like fingerprint, face, ear.

Biometrics is the science of identifying or verifying the identity of a person based on physiological or behavioral characteristics. Biometrics offer much higher accuracy than the more traditional ones. Possession can be lost, forgot or replicated easily. Knowledge can be forgotten. Both possessions and knowledge can be stolen or shared with other people. In biometrics these drawbacks do exist only in small scale. [4]

The ear has been proposed as a biometric [3] .The difficulty is that we have several adjectives to describe e.g. faces but almost none for ears. We all can recognize people from faces, but we hardly can recognize anyone from ears.

Ear biometrics are often compared with face biometrics [7]. Ears have several advantages over complete faces: reduced spatial resolution, a more uniform distribution of color, and less variability with expressions and orientation of the face. In face recognition there can be problems with e.g. changing lightning, and different head positions of the person. [5] There are same kinds of problems with the ear, but the image of the ear is smaller than the image of the face, which can be an advantage.

In practice ear biometrics aren't used very often. There are only some cases in the crime investigation area where the earmarks are used as evidence in court. However, it is still inconclusive if the ears of all people are unique. There are some researches done [6], which favor that ear uniqueness is good enough. [3]

The paper is organized as follows: we start with defining basic terminology of biometrics, then present the structure of the ear and categories of different methods of ear biometrics. The principal component analysis (PCA) algorithm in ear recognition is presented with two different cases.

1.2 Personal Identification, Authentication And Biometrics

There are several application areas where biometrics can be used. Basically there are two types of application scenarios: *identification* (also known as *recognition*, "Who I am?") and *authentication* (also known as *verification*, "Am I who I claim I am?") [3]. In identification there is a database with biometrics and the just taken biometric, e.g. hand shape is compared with the biometrics in database. In authentication the comparison is done only with data, which is known to be valid for the approved person, e.g. the fingerprint or hand shape is included in an identification card. The card will be entered first to the system. After that the system verifies that the new biometric is valid with the one which was in the identification card [5] . The most commonly used biometrics according to Ratha, Senior and Bolle (2001) are fingerprints, face, voice, iris, signature, and hand geometry. Ear biometrics are not commonly used, yet. Fingerprints, face, iris and hand geometry are physiological characteristics.

An ideal biometric is *universal*, *unique*, *permanent* and *collectable*. This means that each person should possess the characteristics (universal) and no two persons should share the characteristics (unique). The characteristics should not change (permanent) and they should be easily presentable to a sensor and quantifiable (collectable). [4]

1.3EAR

Using ear in person identification has been interesting at least 100 years. However, there's no clear evidence that ears are unique. The ear structure is quite complex (see figure 1), but the question is, if it is unique for all individuals.

The most famous work among ear identification is made by Alfred Iannarelli at 1989, when he gathered up over 10.000 ears and found that they all were different [5]. Already at 1906 Imhofer found that in the set of 500 ears only 4 characteristics was needed to state the ears unique [3]

A biometric specialist company Bromba GmbH (2003) has compared different biometrics including ear shape. In the table 1 the constancy of different biometrics is compared. The reasons for variation over time are e.g. growth, aging, dirt, and injury. In a good biometric there is as little as variation possible. According to table 1 ear biometrics based on ear form are averagely permanent: already used biometrics like iris, retina and DNA are more permanent than ear form. At the same level are e.g. fingerprint and hand geometry. Less permanent than ear form are e.g. signature, facial structure and voice.

1.4 Ear Biometrics Methods

There are at least three methods for ear identification: (i) taking a *photo* of an ear, (ii) taking "*earmarks*" by pushing ear against a flat glass and (iii) taking *thermogram pictures* of the ear. The most interesting parts of the ear are the outer ear and ear lope, but the whole ear structure and shape is used.

Taking photo of the ear is the most commonly used method in research. The photo is taken and it is combined with previous taken photos for identifying a person. The earmarks are used mainly in crime solving. Even though some judgments are made based on the earmarks, currently they are not accepted in courts. The thermogram pictures could be one solution for solving the problem with e.g. hair of hat.

Photo comparison

Alfred Iannarelli has made two large-scale ear identification studies in 1989. In the first study there were over 10,000 ears drawn from a randomly selected sample in California. The second study was for researching identical and non-identical twins. These cases support the hypothesis about ear uniqueness. Even the identical twins had similar, but not identical, ear physiological features [5].

Alfred Iannarelli had been working 30 years as deputy sheriff in Alameda County, California, as the chief of the campus police at California State University at Hayward, and in several other law enforcement positions. He became interested in ears in 1948 and over the next 14 years classified about 7,000 ears from photographs. The first version of the book describing his classification method was published 1964. The second edition was published in 1989. Iannarelli does not have academic background for his studies [4].

Alfred Iannarelli has created a 12 measurement "Iannarelli System" (see figure 2). He uses the right ear of people, specially aligns and normalizes the photographs. To normalize the pictures, they are enlarged until they fit to the predefined easel.

After that the measurements are taken directly from the photographs. The distance between each of the numbered areas (figure 3) is measured and assigned an integer distance value. The identification consists of the 12 measurements and the information about sex and race. Burge and Burger (1998) comment that the method is not suitable for machine vision because of the difficulty of localizing the anatomical points. If the first point is not defined accurately, none of the measurements are useful. Iannarelli himself has also recognized this weakness of his system.

After Iannarelli's classification there have become different, more scientific methods for ear identification. Victor et al. (2002) and Chang et al. (2003) have used principal component analysis (PCA) and FERET evaluation protocol for their research about the ears. We will later focus on these researches.

[9] presented multiple identification method, which combines the results from several neural classifiers using feature outer ear points, information obtained from ear shape and wrinkles, and macro features extracted by compression network. They also introduce three different classification techniques for outer ear or auricle identifying.

In [3], the authors have researched automating ear biometrics with Voronoi diagram of its curve segments. They have used a novel graph matching based algorithm for authentication, which takes into account the possible error curves, which can be caused by e.g. lightning, shadowing and occlusion.

Hurley, Nixon and Carter (2000a, 2000b) have used force field transformations for ear recognition. The image is treated as an

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array of Gaussian attractors that act as the source of the force field. According to the researchers this feature extraction technique is robust and reliable and it possesses good noise tolerance.

Earmarks

Ear identification can be done from photographs or from video. There is another possibility: the ear can be pressed against some material, e.g. glass, and the 'earmark' can be used as a biometric. This has been used in crime solving. In England four delinquents have been judged between 1996-1998 by using only the earmarks [3]. However In The Netherlands the court decided that the earmarks are not reliable enough for judging [1] The Dutch found out that the earmarks usually doesn't have enough details for reliable identification. Also when there are no dependable proofs that ears are unique, it was decided that ear identification cannot be used as evidence.

Thermogram pictures

In case the ear is partially occluded by hair the hair can be masked out of the image by using thermogram pictures (see figure 4). In the thermogram pictures different colors and textures are used to find different parts of hear. In figure 3 the subject's hair is between 27.2 and 29.7 degrees Celsius while the outer ear areas range from 30.0 to 37.2 degrees Celsius. The ear is quite easy to detect and localizable using thermogram imagery by searching high temperature areas. [3]

Principal Component Analysis In Ear Recognition

In [5], the authors have made a comparison between face and ear recognition. They used principal component analysis (PCA, also known as "eigenfaces"), which is a dimensionality-reduction technique in which variation in the dataset is preserved. The classification is done in eigenspace, which is a lower dimension space defined by principal components or the eigenvectors of the data set.

The process consists of three steps: i) Preprocessing, ii) Normalization, and iii) Identification (See figure 5 for more details).

In the preprocessing step the ear images are cropped to a size of 400x500 pixels (face images to 768x1024). Coordinates of two distinct points are supplied to the normalization routine: Triangular Fossa and the Antitragus. The normalization step includes geometric normalization, masking and photometric normalization. In this phase all the images are scaled to a standard 130x150 size. Next all non-ear areas, like hair, background etc. are masked. Different levels of masking are experimented for finding the best one to get as good performance as possible for the algorithm. Finally the images are normalized for illumination.

There are two phases in the identification phase: training and testing. In the training phase the eigenvalues and eigenvectors of the training set are extracted and the eigenvectors are chosen based on the top eigenvalues. [6] have decided not to use any specific gallery but have a general representation of both ears and faces. Training set is a set of clean images without any duplicates. In the testing phase the algorithm is provided a set of known ears and faces and a set of unknown ears and faces as the probe set. The algorithm matches each probe to its possibly identity in the gallery.

The ear and face images were collected at the University of South Florida. There were totally 294 subjects with 808 ear images in the experiment, of which half of the ear pictures were left and half right ear. Some of the images were from the same person but taken in different days for testing the day variation of the ears. Every subject had a face image in the database and a corresponding ear image taken under the same conditions as the face image. This is a requirement for reasonable comparison and evaluation. Victor, [6] refer to an article by [3] when stating that all the lightning arrangement and positions of light, cameras and subject follow the FERET face image acquisition protocol.

There were three experiments performed to test this hypothesis: (i) gallery and probe images taken same day with different expression, (ii) gallery and probe images taken in different days with normal expression, and (iii) gallery and probe images taken different day as normal and different expressions (table 2).

Face-based recognition gives better performance than ear-based recognition in all three experiments [6]

Another evaluation

In [3], the authors have made another comparison between ear and face images in appearance-based biometrics. The process is same as in the research of Victor et al. (see Figure 5). PCA was used and the evaluation was done as in FERET approach. There were 197 subjects in the training set; each had both face image and ear image taken under the same conditions and the same image acquisition session. If the face or ear was covered in the picture, they were leaved out from this research.

There were three experiments: (i) day variation experiment, (ii) lightning condition variation experiment, and (iii) pose variation experiment with 22,5 degree rotation. The null hypothesis was that there is no significant difference between using the face or the ear as a biometric when using the same PCA-based algorithm, same subject pool and controlled variation in the used images.

The final result was that the recognition rate for ears was 71.6 percent and for face 70.5 percent. The difference is not statistically significant using a McNemar test [9].

1.5 Application Scenarios

There are several application areas where biometrics can be used either in identification or authentication. In identification the characteristic is compared with characteristics in a database for identifying who the person is. In authentication the characteristic of the person is in e.g. an ID card and this valid information is combined with the new one [8].

Biometrics can be used e.g. when collecting a child from daycare or boarding an aircraft or anything else between them [6]. A typical example of using biometrics is an automatic teller machine (ATM). In this vision the user inserts the bankcard and types the personal identification number (PIN). Simultaneously the camera records the face and ear and the identity of the person will be supplementary verified. So not only the bankcard and the PIN have to be compatible with each other, but also the used biometrics have to fit in [9].

Passive ear biometrics are ideal with different security levels. Currently access rights are handled mainly with different kinds of identity cards with passive transmitters. Anyone who gets the card can use it. In some cases there can be video cameras, which record the people who use the card. However it is not real time system. Using passive ear biometrics no person is allowed to enter restricted area without recognition the person. In the case two attempts of identification do not match, a camera is activated and linked to the security counsel's office. The security personnel can visually combine the picture in the database and the taken picture and decide if the person is allowed to enter to the restricted area [5].

In [9], the authors have researched the ability to identify a person from surveillance videotapes. There were many robberies of gas stations in The Netherlands. The offender was wearing a baseball cap, shawl and a cloth hanging from the cap to his face so that the face was covered. However the ears were visible. This is the fact that raised the question is people can be identified just from ear. The quality of the videotapes is increasing, which supports the possibility to use ear identification.

Applications using biometrics are more secure than traditional user name and password combinations. A requirement for personal identification systems is cost effectiveness: the systems should work with standard video and computer hardware. An advantage compared with e.g. retinal and iris scan is that ear recognition is less intrusive. In [5], the authors presented that an ideal biometric should be universal, unique, permanent and collectable. However in practice, a characteristic that satisfies all these requirements, may not be suitable for a biometric system. In biometric systems there are more requirements, e.g. *performance*, *acceptability* and *circumvention*.

Performance means system's accuracy and speed. If the system is too slow and it makes too many mistakes, the system won't be used. Acceptability is important: if the people don't accept the systems as a part of their daily routines, the system won't be used. Circumvention is that how easy it is to fool the system. This rate should be very low, otherwise the advantage of the system is low [2].

For using ear identification in real life applications it is also needed, that the facilities, e.g. surveillance video cameras, will be good quality enough and the costs won't be too high [5].

When using biometrics for authentication purposes there are several viewpoints to taken into account. The system has to be *Comfort*, which means that the duration of the verification has to be as low as possible and the system must be easy to use. It also has to be *Accurate* so that the error rate is as low as possible. The system has to be *Available* when needed and where needed. The *Costs* of the system affects also to the use of biometric system [9].

As seen in the table 3, the most suitable biometrics for person authentication would be iris. The DNA would be good otherwise but the duration of the authentication process is too long for everyday use. The ear form is in the average class in all the four parameters.

Application: Video based ear identification in gas station robbery using visual identification

In [6], the authors from The Netherlands' Forensic Institute describe a small experiment, where the goal was to find out if a gas station robbery could be solved by using VHS quality ear pictures and ear identification. The video about the perpetrator was taken with Times Laps surveillance cameras using VHS-video recorder. There were 22 voluntaries, which were put in the front of the cameras wearing same type of overall as the perpetrator.

The setup was motivated by several aspects, e.g. camera positions, lightning, position and movement of the perpetrator and other uncontrollable factors. Before presenting the video clips, they were digitalized and put on computer. All other body parts except the ear was masked, so no other characteristics, e.g. size, gait, height, wouldn't affect to the identification process.

The respondents participating in the test were presented 40 sets of two video film clips and asked, (i) do you think there is enough information in these video films to make an individualization or exclusion, and (ii) is the person in this video the same than in previous videos.

The results were that there were significant percentage of false identifications. However the formal Chi-square tests show that the choice is clearly better than random. For more details, see [8].

1.6 Error Possibilities In Ear Identification

There are several error possibilities in ear identification. Basically the human ear shape is the same during the whole life and the growth is proportional. However, the gravity can cause ear stretching. The stretching is about five times greater from age of four months to age of eight years and again after about 70 years. The ear can be covered e.g. with hair or a hat [6]. Also the lightning and pose variation can cause error situations (see figure 6).

In identification the idea is to check if the biometrics extracted from the picture sufficiently matches with the previously acquired ones. Because there are changes in the environment and the subject, some tolerance has to be accepted. This tolerance can be defined in terms of *false reject rate* (FRR) and the *false acceptance rate* (FAR), exhibited by the system.

Usually one of the two is trying to be minimized depending on the required security level. [8]

Measuring the absolute measurements can decrease the FAR value. [6] have found that the lengths of the art curves are not reliable because there are some small variations depending on the lightning. More reliable measurement is the width of an ear curve corresponding to the upper Helix rim (figure 7). This can be reliably extracted and normalized against the height of the ear.

[6]have found that most of the false curves in the graph model are caused by inner cavity (see Figure 8). The main reason is that in the area there’s oil and wax build ups, which cause misguiding shadows. The false curves are removed. This can break the remaining curves so we have to merge the neighbor curves. [6]

The main problem with using ear biometrics is that they are not usable if the ear is covered e.g. with a hat or hair. In active identification systems the subject can take the hat of or pull their hair back for authentication. The main problem occurs in passive identification systems. One possibility is to use thermogram images, where the colors in the picture tell the temperature of the segment. In this idea [9] use the fact that the temperature of hair is lower that the temperature of the ear.

However, the temperature in the outermost parts of the ear can be quite similar with the temperature of hair. In many cases by searching the high temperature parts it is possible to localize the ear.

2. Ear Preprocessing

This section is an introduction on how to handle images in Matlab. When working with images in Matlab, there are many things to keep in mind such as loading an image, using the right format, saving the data as different data types, how to display an image, conversion between different image formats, etc. This chapter presents some of the commands designed for these operations. Most of these commands require you to have the *Image processing tool box* installed with Matlab. To find out if it is installed, type ver at the Matlab prompt. This gives you a list of what tool boxes that are installed on your system.

For further reference on image handling in Matlab you are recommended to use Matlab's help browser. There is an extensive (and quite good) on-line manual for the Image processing tool box that you can access via Matlab's help browser.

2.2 Fundamentals

A digital image is composed of *pixels* which can be thought of as small dots on the screen. A digital image is an instruction of how to color each pixel. We will see in detail later on how this is done in practice. A typical size of an image is 512-by-512 pixels. Later on in the course you will see that it is convenient to let the dimensions of the image to be a power of 2. For example, 2^9=512. In the general case we say that an image is of size *m*-by-*n* if it is composed of *m* pixels in the vertical direction and *n* pixels in the horizontal direction.

Let us say that we have an image on the format 512-by-1024 pixels. This means that the data for the image must contain information about 524288 pixels, which requires a lot of memory! Hence, *compressing* images is essential for efficient image processing. You will later on see how Fourier analysis and Wavelet analysis can help us to compress an image significantly. There are also a few "computer scientific" tricks (for example entropy coding) to reduce the amount of data required to store an image.

Image formats supported by Matlab

The following image formats are supported by Matlab:

1. BMP
2. HDF
3. JPEG
4. PCX
5. TIFF
6. XWB

Most images you find on the Internet are JPEG-images which is the name for one of the most widely used compression standards for images. If you have stored an image you can usually see from the suffix what format it is stored in. For example, an image named myimage.jpg is stored in the JPEG format and we will see later on that we can load an image of this format into Matlab.

2.3 Working formats in Matlab

If an image is stored as a JPEG-image on your disc we first read it into Matlab. However, in order to start working with an image, for example perform a wavelet transform on the image, we must convert it into a different format. This section explains four common formats.

Intensity image (gray scale image)

This is the equivalent to a "gray scale image" and this is the image we will mostly work with in this course. It represents an image as a matrix where every element has a value corresponding to how bright/dark the pixel at the corresponding position should be colored. There are two ways to represent the number that represents the brightness of the pixel: The double class (or data type). This assigns a floating number ("a number with decimals") between 0 and 1 to each pixel. The value 0 corresponds to black and the value 1 corresponds to white. The other class is called uint8 which assigns an integer between 0 and 255 to represent the brightness of a pixel. The value 0 corresponds to black and 255 to white. The class uint8 only requires roughly 1/8 of the storage compared to the class double. On the other hand, many mathematical functions can only be applied to the double class. We will see later how to convert between double and uint8.

Binary image

This image format also stores an image as a matrix but can only color a pixel black or white (and nothing in between). It assigns a 0 for black and a 1 for white.

Indexed image

This is a practical way of representing color images. (In this course we will mostly work with gray scale images but once you have learned how to work with a gray scale image you will also know the principle how to work with color images.) An indexed image stores an image as two matrices. The first matrix has the same size as the image and one number for each pixel. The second matrix is called the *color map* and its size may be different from the image. The numbers in the first matrix is an instruction of what number to use in the color map matrix.

RGB image

This is another format for color images. It represents an image with three matrices of sizes matching the image format. Each matrix corresponds to one of the colors red, green or blue and gives an instruction of how much of each of these colors a certain pixel should use.

Multiframe image

In some applications we want to study a sequence of images. This is very common in biological and medical imaging where you might study a sequence of slices of a cell. For these cases, the multiframe format is a convenient way of working with a sequence of images. In case you choose to work with biological imaging later on in this course, you may use this format.

How to convert between different formats

The following table shows how to convert between the different formats given above. *All these commands require the Image processing tool box!* The command mat2gray is useful if you have a matrix representing an image but the values representing the gray scale range between, let's say, 0 and 1000. The command mat2gray automatically re scales all entries so that they fall within 0 and 255 (if you use the uint8 class) or 0 and 1 (if you use the double class).

How to convert between double and uint8

When you store an image, you should store it as a uint8 image since this requires far less memory than double. When you are processing an image (that is performing mathematical operations on an image) you should convert it into a double. Converting back and forth between these classes is easy.

I=im2double(I);

converts an image named I from uint8 to double.

I=im2uint8(I);

converts an image named I from double to uint8.

2.4 How to read files

When you encounter an image you want to work with, it is usually in form of a file (for example, if you down load an image from the web, it is usually stored as a JPEG-file). Once we are done processing an image, we may want to write it back to a JPEG-file so that we can, for example, post the processed image on the web. This is done using the imread and imwrite commands. *These commands require the Image processing tool box!*

Make sure to use semi-colon ; after these commands, otherwise you will get LOTS OF number scrolling on you screen... The commands imread and imwrite support the formats given in the section "Image formats supported by Matlab" above.

Loading and saving variables in Matlab

This section explains how to load and save variables in Matlab. Once you have read a file, you probably convert it into an intensity image (a matrix) and work with this matrix. Once you are done you may want to save the matrix representing the image in order to continue to work with this matrix at another time. This is easily done using the commands save and load. Note that save and load are commonly used Matlab commands, and works independently of what tool boxes that are installed.

Examples

In the first example we will down load an image from the web, read it into Matlab, investigate its format and save the matrix representing the image.

Example 1.

Down load the following image (by clicking on the image using the right mouse button) and save the file as cell1.jpg.

This is an image of a cell taken by an electron microscope at the Department of Molecular, Cellular and Developmental Biology at CU.

Now open Matla and make sure you are in the same directory as your stored file. (You can check what files your directory contains by typing ls at the Matlab prompt. You change directory using the command cd.) Now type in the following commands and see what each command does. (Of course, you do not have to type in the comments given in the code after the % signs.)

Note that all variables that you save in Matlab usually get the suffix .mat.

Next we will see that we can display an image using the command imshow. This command requires the image processing tool box. Commands for displaying images will be explained in more detail in the section "How to display images in Matlab" below.

```
clear % Clear Matlab's memory.
load I % Load the variable I that we saved above.
whos % Check that it was indeed loaded.
imshow(I) % Display the image
I=im2double(I); % Convert the variable into double.
whos % Check that the variable indeed was converted into double

% The next procedure cuts out the upper left corner of the image
% and stores the reduced image as Ired.

for i=1:256
for j=1:256
Ired(i,j)=I(i,j);
end
end

whos % Check what variables you now have stored.
imshow(Ired) % Display the reduced image.
```

```
I=rgb2gray(I); % Convert to gray scale
imshow(I)
```

Now the size indicates that our image is nothing else than a regular matrix.
Note: In other cases when you down load a color image and type whos you might see that there is one matrix corresponding to the image size and one matrix called map stored in Matlab. In that case, you have loaded an indexed image (see section above). In order to convert the indexed image into an intensity (gray scale) image, use the ind2gray command described in the section "How to convert between different formats" above.

2.5 How to display an image in Matlab
Here are a couple of basic Matlab commands (do not require any tool box) for displaying an image.

Sometimes your image may not be displayed in gray scale even though you might have converted it into a gray scale image. You can then use the command colormap(gray) to "force" Matlab to use a gray scale when displaying an image.
If you are using Matlab with an Image processing tool box installed, I recommend you to use the command imshow to display an image.

2.6 Prewitt edge detection
Prewitt is a method of edge detection in image processing which calculates the maximum response of a set of convolution kernels to find the local edge orientation for each pixel. Various kernels can be used for this operation. The whole set of 8 kernels is produced by taking one of the kernels and rotating its coefficients circularly. Each of the resulting kernels is sensitive to an edge orientation ranging from 0° to 315° in steps of 45°, where 0° corresponds to a vertical edge.

The maximum response for each pixel is the value of the corresponding pixel in the output magnitude image. The values for the output orientation image lie between 1 and 8, depending on which of the 8 kernels produced the maximum response.

This edge detection method is also called edge template matching, because a set of edge templates is matched to the image, each representing an edge in a certain orientation. The edge magnitude and orientation of a pixel is then determined by the template that matches the local area of the pixel the best.

The Prewitt edge detector is an appropriate way to estimate the magnitude and orientation of an edge. Although differential gradient edge detection needs a rather time-consuming calculation to estimate the orientation from the magnitudes in the x- and y-directions, the Prewitt edge detection obtains the orientation directly from the kernel with the maximum response. The set of kernels is limited to 8 possible orientations; however experience shows that most direct

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orientation estimates are not much more accurate.

On the other hand, the set of kernels needs 8 convolutions for each pixel, whereas the set of kernel in gradient method needs only 2, one kernel being sensitive to edges in the vertical direction and one to the horizontal direction. The result for the edge magnitude image is very similar with both methods, provided the same convolving kernel is used.

Mathematically, the operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives - one for horizontal changes, and one for vertical. If we define as the source image, and and are two images which at each point contain the horizontal and vertical derivative approximations, the latter are computed as:

$$\mathbf{G_x} = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} * \mathbf{A} \quad \text{and} \quad \mathbf{G_y} = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ +1 & +1 & +1 \end{bmatrix} * \mathbf{A}$$

3. Ear Recognition System

Biometrics is the science in which an entity is distinguished on the basis of physiological features or behavioural characteristics [1]. Physiological characteristics include finger print, iris scan, retina scan, face, thermo grams of face, palm print, ear etc. whereas behavioral characteristics consist of gait recognition, odour, voice recognition and signature verification. The results are obtained in biometrics by using single or multiple means.

The achieved results indicate that biometric techniques are much more precise and accurate than the traditional techniques. Other than precision, there have always been certain problems which remain associated with the existing traditional techniques.

As an example consider possession and knowledge. Both can be shared, stolen, forgotten, duplicated, misplaced or taken away. However the danger is minimized in case of biometric means [2].

The role of biometrics is amenable in all types of security systems. With the threats/advances of technologies, there is always need to search new means for using as stand-alone applications or in conjunction with the xisting systems. In order to include any new class of biometric, the ondition required is that it should be universal, distinct, everlasting and ollectable i.e. all individuals must have those features (universal) and these features should be identifiable for each individual (distinct).

The features should not vary (everlasting) and it must be easy to get required information from these features (collectable) [3]. It is obvious that ears are a prominent feature of all persons making it universally acceptable. Ear biometrics has several advantages over complete face: reduced spatial resolution, a more uniform distribution of colors and less variability with expressions and orientation of the face.

In the present chapter, a new ear recognition approach using neural network is applied for human identification.

3.2 Background and related work

Ear was first used for recognition of human being by Iannarelli [4] who used manual techniques to identify ear images. Samples of over 10,000 ears were studied to prove the distinctiveness of ears. Structure of ear does not change radically over time.

The medical literature [4] provides information that ear growth is proportional after first four months of birth and changes are not noticeable in the age 8 to 70. Victor et al. [5] and Chang et al. [6] used eigen ear for identification.

The results obtained were different in both cases. Chang's results show no difference in ear and face performance while Victor's results show that ear performance is worse than face.

According to Chang views, the difference in result might be due to usage of different image quality. Moreno et al. [2] used 2D intensity images of ears with three neural net approaches (Borda, Bayesian, Weighted Bayesian combination) for recognition. In his work, 6 images from 28 people were used to evaluate the recognition rate of about 93%. Chen et al. [7] studied two steps iterative closest point algorithm on 30 people with their 3D ear images that were manually extracted.

The results reveal 2 incorrect matching out of 60 images. The methology adopted for ear recognition in this paper is explained by Figure 9. Main blocks are preprocessing, feature extraction, training and matching. The details are given in the coming sections.

3.3 Preprocessing

Images with ear rings, other artifacts and occluded with hairs have not been processed in this research work. Each image is gone through the following steps before feature extraction.

- Ear image is *cropped manually* from the complete head image .
- Cropped ear image is resized.
- Coloured image is converted to grayscale image.

Manual cropping has been done in the work because automated ear cropping is under process. The sizes of cropped ear image are different. In order to find same number of features from each ear image, resizing the images to unique fixed size of 64*64 pixels is made.

Each image was converted from RGB to grayscale (if not in grayscale). Then it was sent to feature extraction module. Figure 10 demonstrates the output at the end of preprocessing step.

3.4 Feature Extraction and Matching

After normalizing the ear images, next step is feature

extraction. One can do not perform such a task as we have the ear only. But we can perform any edge detection to get the ear-print. The used one is perwitt.

The proposed method is implemented in MATLAB7.0 on a PC with 1.6 GHz Intel processor and 256 MBRAM. The over all system architecture is shown next.

4. Ear Matching

Ear matching is a difficult problem due to the large intra-class variations (variations among different impressions) and the small inter-class variations (different images may appear quite similar). Three fundamental reasons for the large intra-class variations are partial overlap, non-linear distortion, and camera noise.

4.1 What is ear matching?

EAR matching refers to finding the similarity between two given images. The choice of the matching algorithm depends on which ear representation is being used. Typically, a matching algorithm first attempts to recover the translation, rotation, and deformation parameters between the given image pair and then between the two images. Due to noise and distortion introduced during ear capture and the inexact nature of feature extraction, the ear representation often has missing, spurious, or noisy features.

4.2 Verification vs. Identification:

A ear recognition system is essentially a pattern recognition system that can be deployed in two different modes:

(1) Verification

(2) Identification.

Verification refers to authenticating the *claimed* identity of a user, while identification refers to establishing the identity of a user**.**

Identification (one-to-*N* matching) is inherently a more difficult pattern recognition problem as it involves an *N*-class classification problem, where *N* is the number of users enrolled in the system. Verification (one-to-one matching) is a relatively easier problem that can be formulated as a simple two class hypothesis testing problem [8]

4.3 How matching occurred?

Given two (input and template) representations, the matching module determines whether the associated prints are impressions of the same ear. The matching phase typically defines a similarity measure between two ear representations .In the ideal case, where

(1) The correspondence between the input and template representations is known,

(2) There are no deformations such as translation, rotation, and distortions between them, and

(3) Features in a ear image can be reliably extracted (correctly localized), ear verification is a relatively simple task of finding the similarity between the two representations [4].

4.4 Matching techniques:

4.4.1 Correlation-based Matching:

The simplest correlation-based technique is to align the two ear images and subtract the input image from the template image to see if the ridges correspond. However, such a simplistic approach suffers from many problems, including the errors in estimation of alignment, nonlinear deformation in ear images, and noise. An autocorrelation technique has been proposed by Sibbald that computes the correlation between the input and the template at fixed translation and rotation increments. Correlation is perfect due to its speed.[3]

The fast normalized cross-correlation [17-58] between the query window and the template window is computed and the peak is detected. If the estimation of rotation and displacement is accurate and there is no non-linear distortion, the peak would occur at the center of the correlation matrix [3].

This model should take into consideration the following factors:

1. The ear may be placed at different locations on the camera, introducing (global) translation between the input and the template representations.
2. The ear may be placed in different orientations on the camera, introducing a (global) rotation between the input and the template representations.
3. The ear may exert a different (average) downward normal pressure on the camera, introducing a (global) spatial scaling between the input and the template representations.
4. The ear may exert a different (average) shear force on the camera, introducing a (global) shear transformation (characterized by a shear direction and magnitude) between the input and the template representations.
5. Spurious features may be present in both the input and the template representations.
6. Genuine features may be absent in both the input and the template representations.

A variant of the correlation technique is to perform the correlation in the frequency domain instead of the spatial domain.

❖ **Advantages of performing correlation in the frequency domain:**

1. Is that it is translation-invariant.
2. The frequency-domain correlation matching can also be performed optically.
3. The input and the template ears are projected via laser light through a lens to produce their Fourier transform.

❖ **Disadvantages of performing correlation in the frequency domain:**

1. Is the extra computation time required to convert the spatial image to a frequency representation?
2. Is that optical processors have very limited versatility (programmability).

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A modification of the spatial correlation-based techniques is to divide the ear images into grids and determine the correlation in each sector instead of the whole image**.** The correlation-based techniques typically require more resources (matching time and template size). Although correlation-based matchers use the more discriminatory information present in the gray-scale ear images, their performance is expected to deteriorate as the time duration between enrollment and verification increases. In fact, the best way to improve performance is to use an appropriate alignment model and combine multiple features, multiple alignment hypotheses, and multiple matching algorithms. It is important to point out that an accurate ear matching algorithm alone does not necessarily result in a good authentication system; a large number of system level. Issues such as camera quality, automatic image capture, enrollment procedure, speed of feature extraction and matching, security and integrity of the system, etc. contribute to the success of the deployed systems.

4.4.2 Neural Network based Matching

What is neural network?

- ***An artificial neural network (ANN),*** usually called "*neural network*" (NN), is a mathematical model or computational model that tries to simulate the structure and/or functional aspects of biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.
- A neural network is an interconnected group of nodes, akin to the vast network of neurons in the human brain.

NN Introduce a variety of benefits that an analyst realizes from using neural networks in their work:

The system is developed through learning rather than programming.

Neural nets teach themselves the patterns in the data freeing the analyst for more interesting work.

Neural networks are flexible in a changing environment. Although neural networks may take some time to learn a sudden change, they are excellent at adapting to constantly changing information.

Although neural networks have mentioned benefits, it can take time to train a model from a very complex data set. Neural techniques are computer intensive and will be slow on low end PCs or machines

- **Types of Neural Nets.**

There are several types of neural nets exist. They can be distinguished by:

- Their type (feed forward or feedback),
- Their structure (single Layer, Multi Layer) ,
- And the learning algorithm they use.

Based on structure, neural networks can be broadly classified into two types:

1. Feed-Forward NNS
2. Feed-back NNS

- **Learning Algorithms:**

Before we can use any neural network, we have to train it. By ***training***, we mean adjusting various parameters such that the network becomes usable. There are various methods in which we can train neural networks.

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Types of Training

I. Supervised Training

In supervised methods of training, neural network expects a set of sample inputs and the desired outputs corresponding to those inputs. After training, the neural network maps ant given input to one of the trained outputs. LVQ training is one of the most widely used supervised training algorithms.

II. Unsupervised training

These methods are used when we are not aware of the possible outputs for given inputs. In these methods, neural network is fed with huge amounts of data and is allowed to try, learn, organize and derive conclusions itself. These methods are used in applications which involve identifying patterns or trends in the input data. (For example, sales forecasting)**.**

NNS Models :

1. Perceptron.
2. Back propagation Net.
3. Hopfield Net.
4. Kohonen Feature Map.

In our project we introduce to use perfect training algorithm which is **back propagation.** In more detailed, feed forward back propagation.

Back propagation Algorithm

The term ***Back propagation*** refers to the manner in which the gradient is computed for nonlinear multilayer networks. There are a number of variations on the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods [9].

There are generally four steps in the training process:

1. Assemble the training data.
2. Create the network object.
3. Train the network.
4. Simulate the network response to new inputs.

Topology

Architecture: multi-layer feedforward backprobagation

Number of input neurons : 1024 correspond to (32 times 32 pixel area on the ear image around a core)

Number of hidden neuron in hidden layer : 10 by guesswork.

Number of output neurons: depends on number of classes (here persons) which are 80.

Training method : log-sigmoid, 'logsig' in matlab

Activation function : momentum gradient decent, 'traingdx' in matlab

Error rate measure : sum of squared error, 'sse' in matlab

Stopping criteria : either error reaches 0.001; or maximum training epochs reaches 5000

However, we tried many topologies before reaching to this topology. Some of these important ones are presented here.

5. Experimental Results

Using ears in identifying people has been interesting at least 100 years. The researches still discuss if the ears are unique or unique enough to be used as biometrics. Ear shape applications are not commonly used, yet, but the area is interesting especially in crime investigation. In chapter I present the basics of using ear as biometric for person identification and authentication. Also the error rate and application scenarios of ear biometrics are presented.

A set of 17 people has been used for experiments having six or more images each. National Institute of Standards and Technology(NIST) Special Database 18, Mugshot Identification Database (MID). NIST Special Database 18 is being distributed for use in development and testing of automated mugshot identification systems. The database consists of three CD-ROMs, containing a total of 3248 images of variable size, compressed with lossless compression. Each CD-ROM requires approximately 530 megabytes of storage compressed and 1.2 gigabytes

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uncompressed (2.2 : 1 average compression ratio). There are images of 1573 individuals (cases), 1495 male and 78 female. The database contains both front and side (profile) views when available. Separating front views and profiles, there are 131 cases with two or more front views and 1418 with only one front view. Profiles have 89 cases with two or more profiles and 1268 with only one profile. Cases with both fronts and profiles have 89 cases with two or more of both fronts and profiles, 27 and 1217 with only one front and one profile.
The correct recognition rate is ranging between 84.3% and 91.2% for artificial neural network matching, it depends on neural network training parameters .

6.Conclusion

An ear recognition neural based algoeithm has been presented. A recognition rate between 84.3% and 91.2% has been achieved by performing neural matching. We can conclude that the recognition rate depends on neural network training parameters. The propoesed algorithm can be used efficiently for personal identification.

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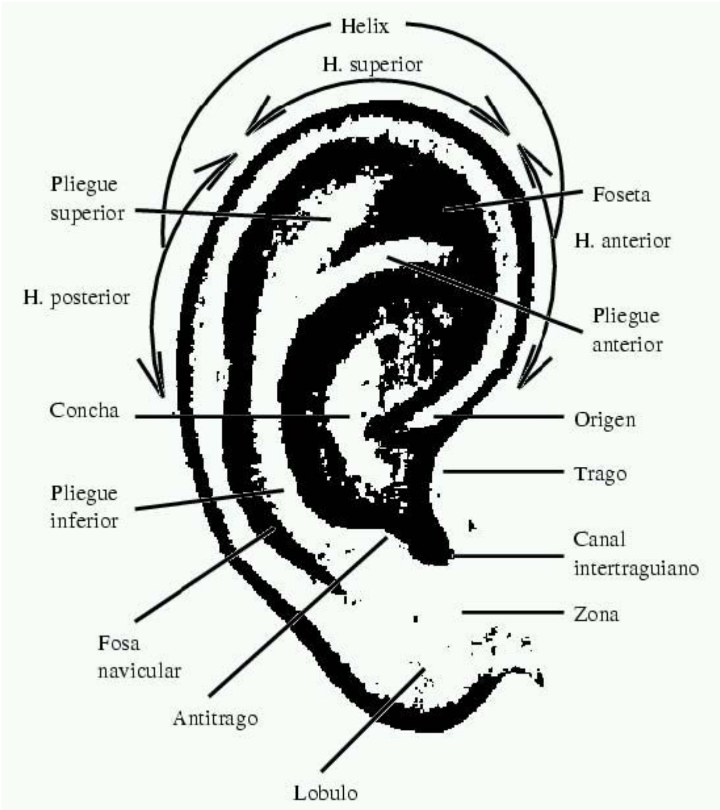


Fig. 1: Ear structure [6].

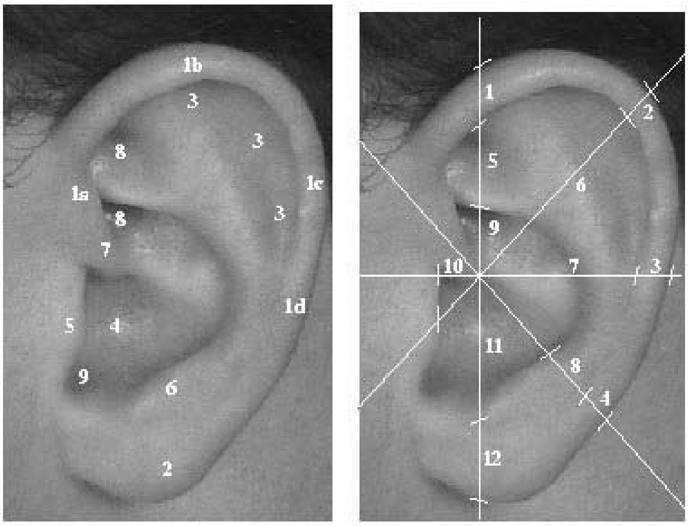


Fig. 2: (a) Anatomy, (b) Measurements. (a) 1 Helix Rim, 2 Lobule, 3 Antihelix, 4 Concha, 5 Tragus, 6 Antitragus, 7 Crus of Helix, 8 Triangular Fossa, 9 Incisure Intertragica. (b) The locations of the anthropometric measurements used in the "Iannarelli System" [6].

Fig. 3: Ear features

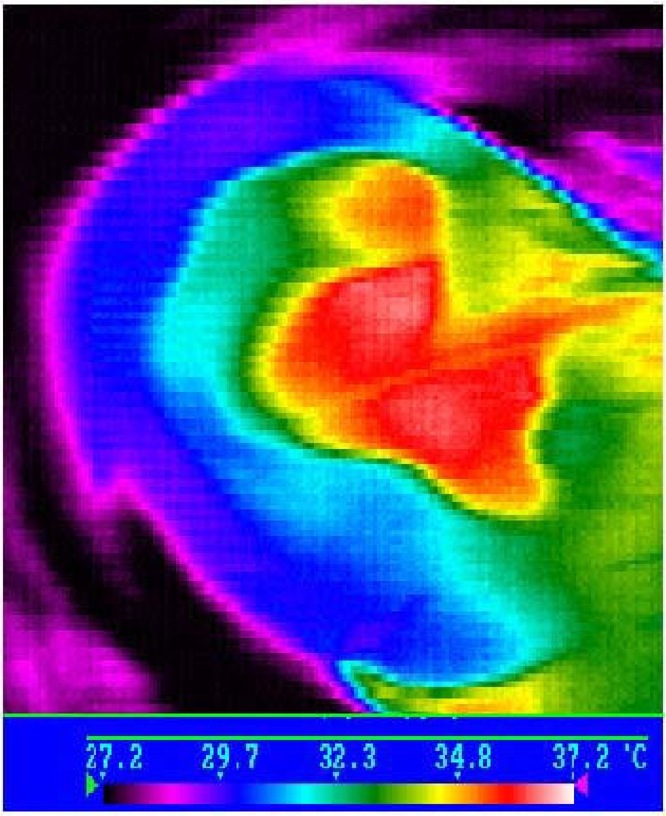


Fig. 4: Thermogram of an ear. Image provided by Brent Griffith, Infrared Thermography Laboratory, Lawrence Berkeley, National Laboratory. [3]

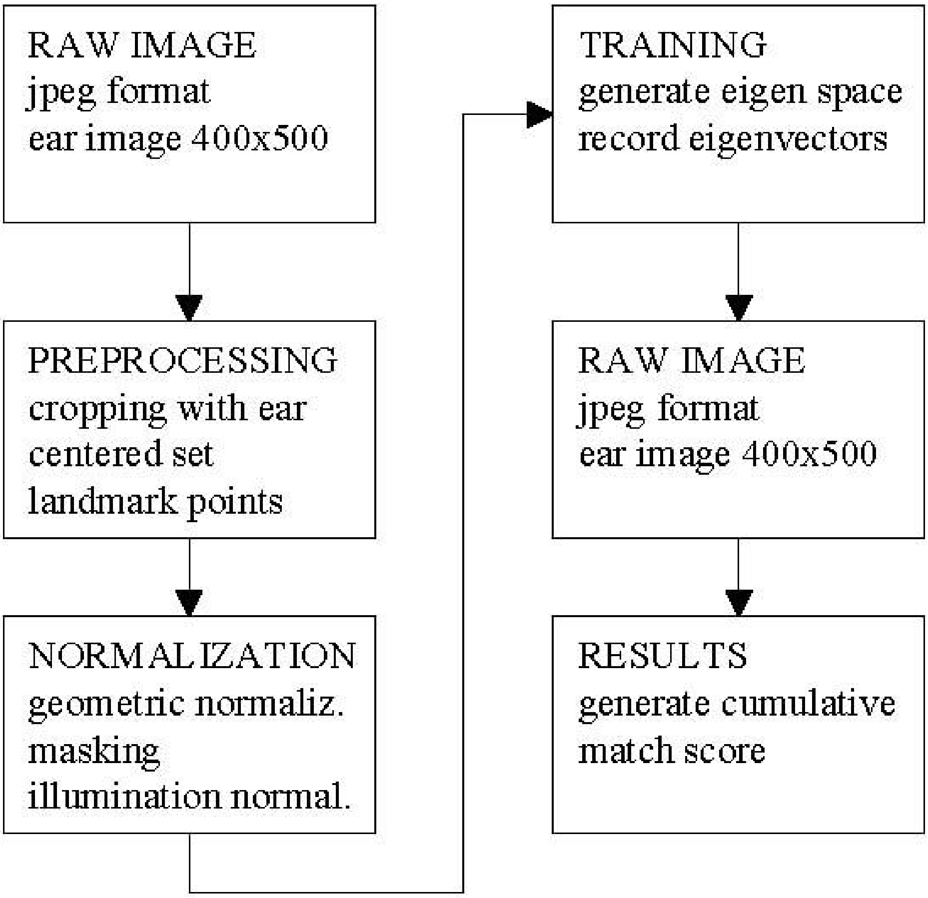


Fig. 5: Steps of PCA method [3].

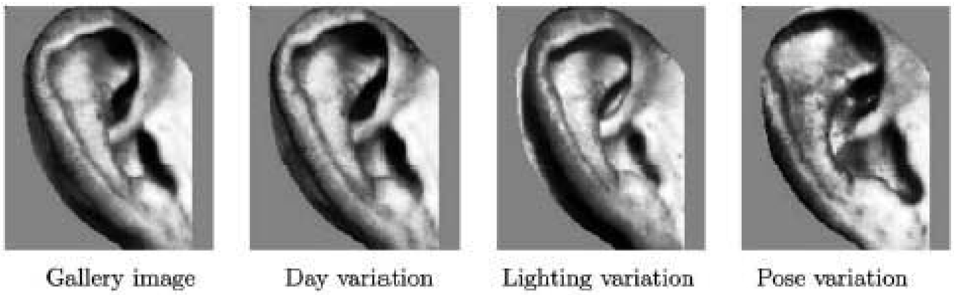


Fig. 6: The same ear can look different depending on e.g. day, lightning or pose variation [5].

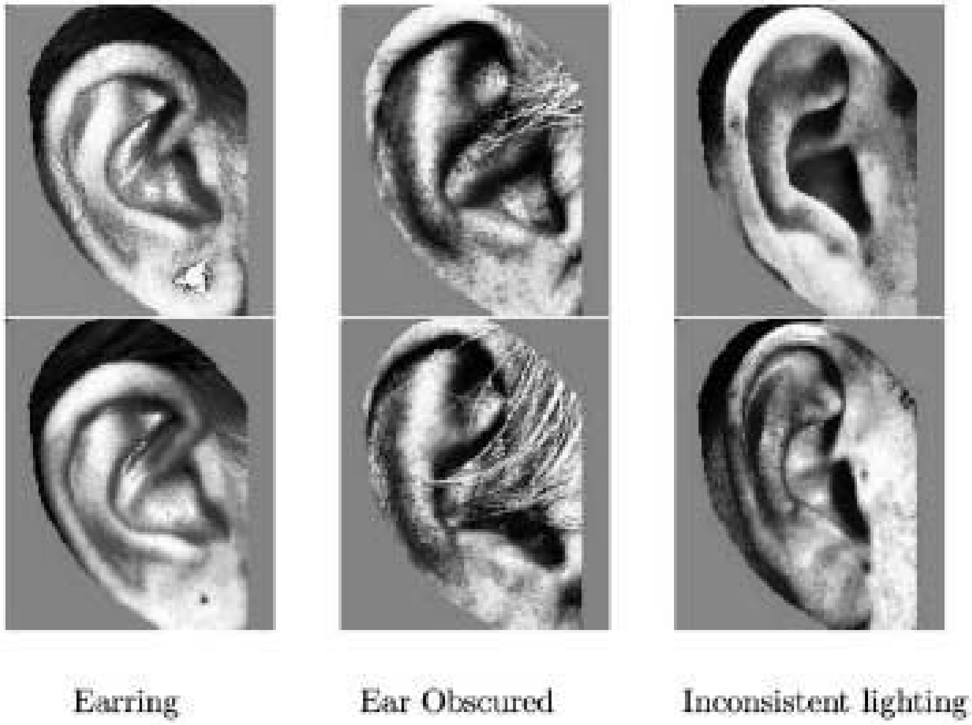


Fig. 7: Error possibilities in ear recognition [5].

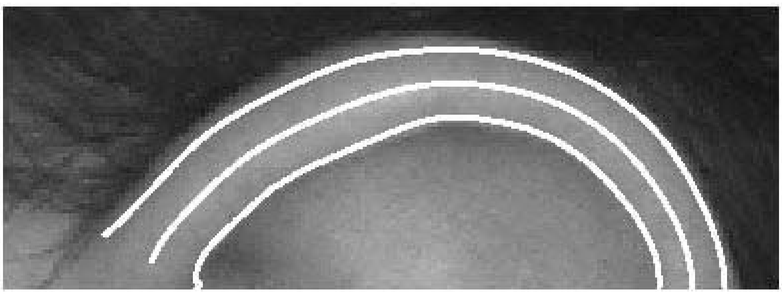


Fig. 8: Improving the FRR with ear curve widths [2].

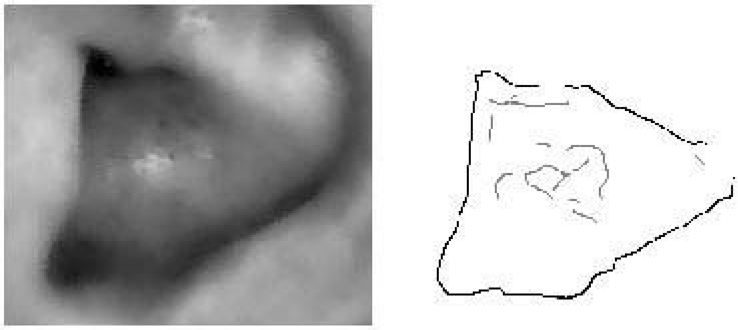
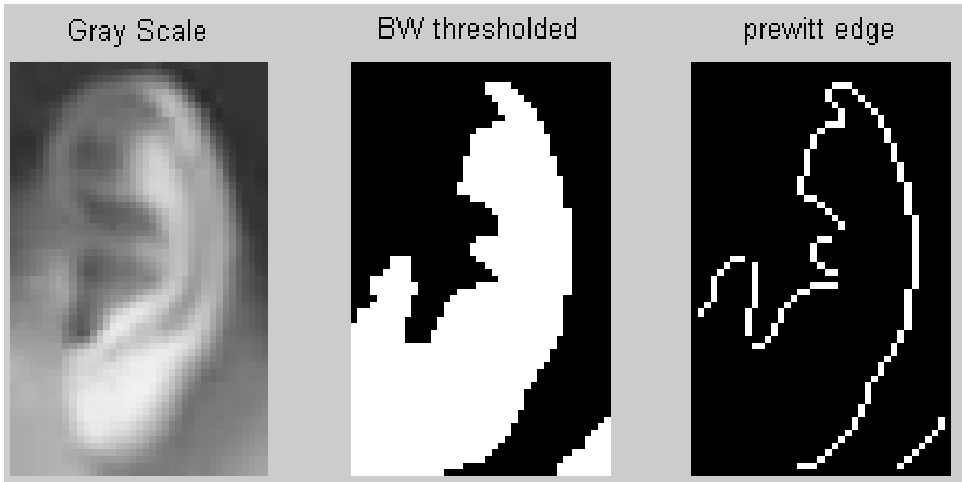


Fig. 9: Removal of noise curves in the inner ear [8].



a) b) c)

Fig 10: preprocessing
a) original image b) BW c) Perwitt

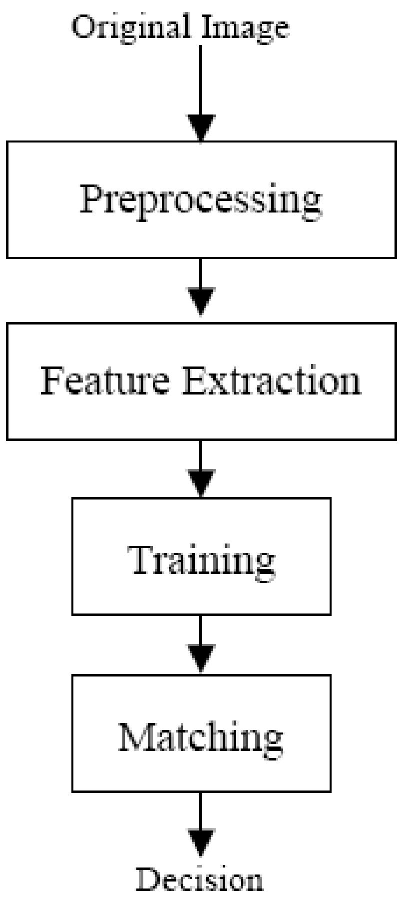


Fig. 11: Steps of the proposed method

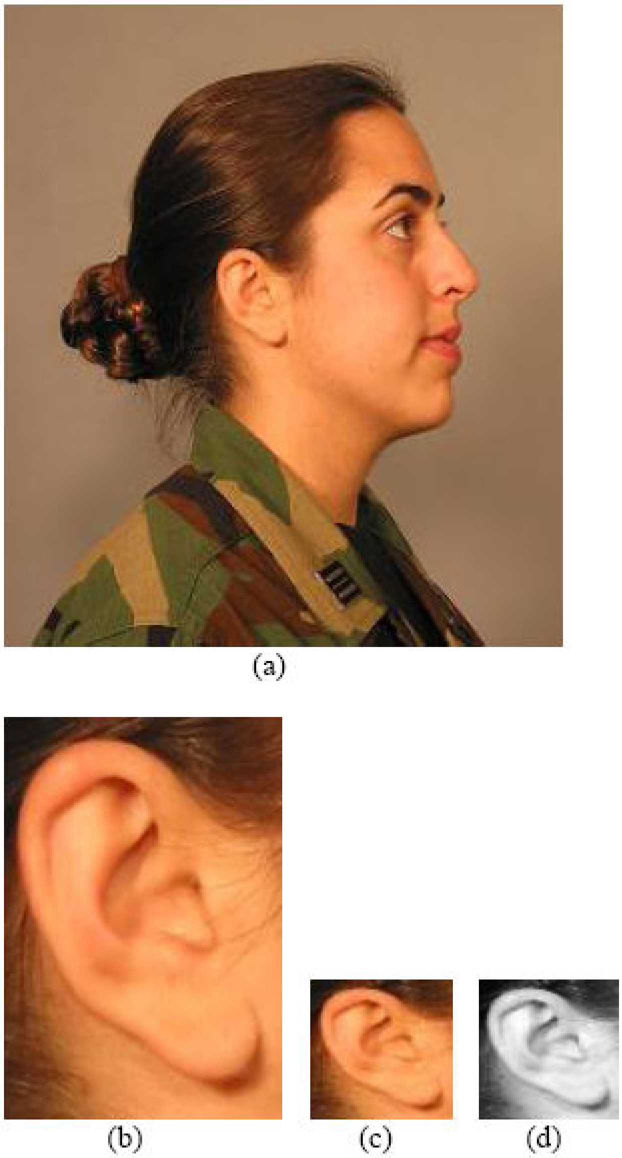


Fig. 12: (a) shows the actual image in the database and cropped image is visible in Figure 12 (b). Figure 12 (c) and Figure 12 (d) are the resized cropped images with RGB and grayscale respectively.

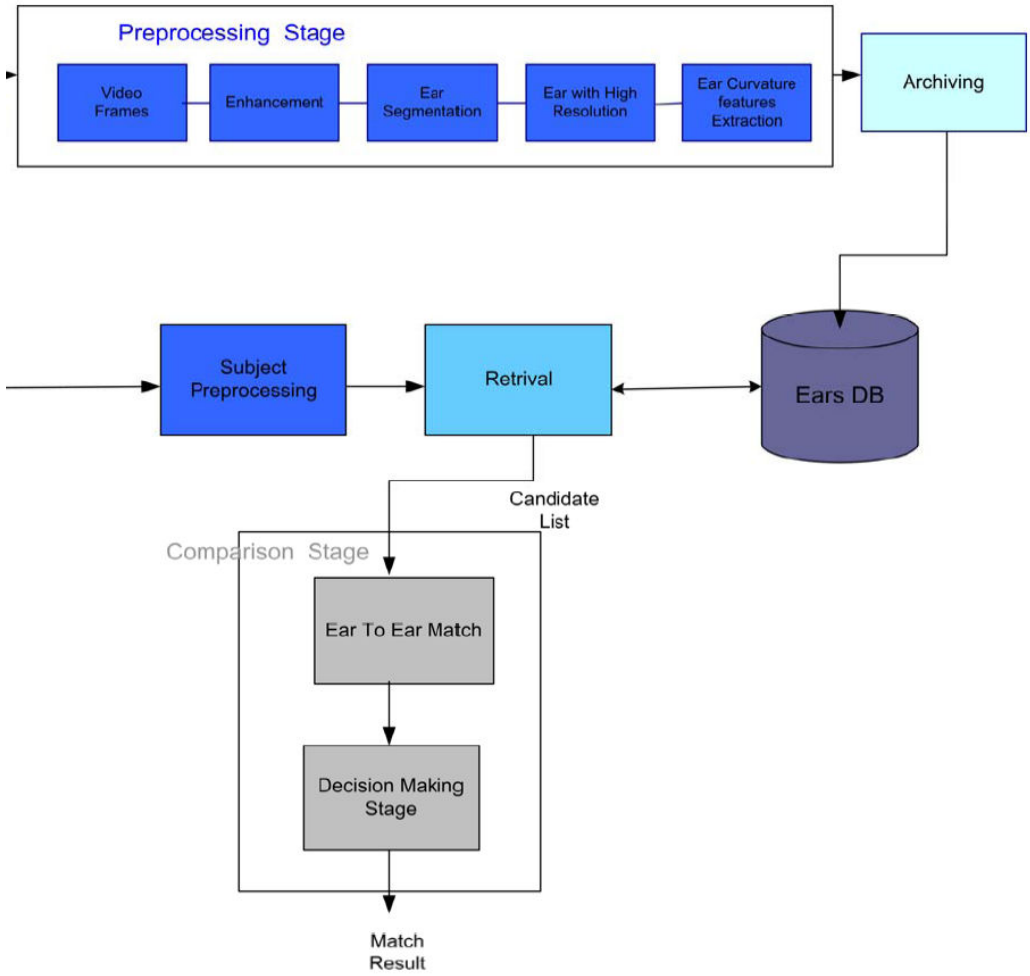


Fig. 13: System architecture

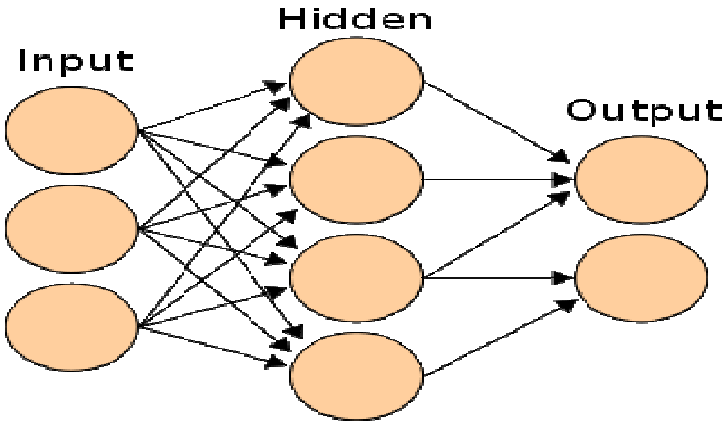


Fig 14: Artificial Neural Structure.

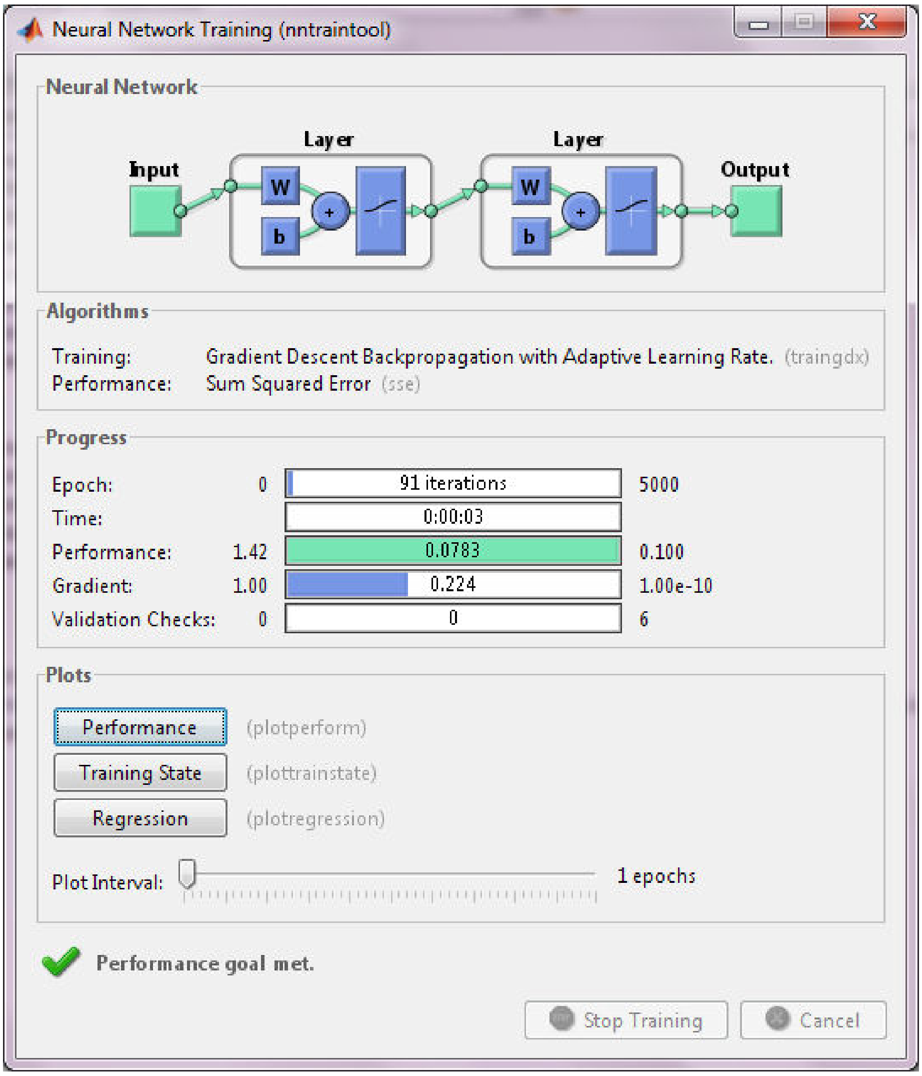


Fig. 15: Back propagation at training.
Activation function : momentum gradient decent, 'traingdx'
Error rate measure : sum of squared error, 'sse'

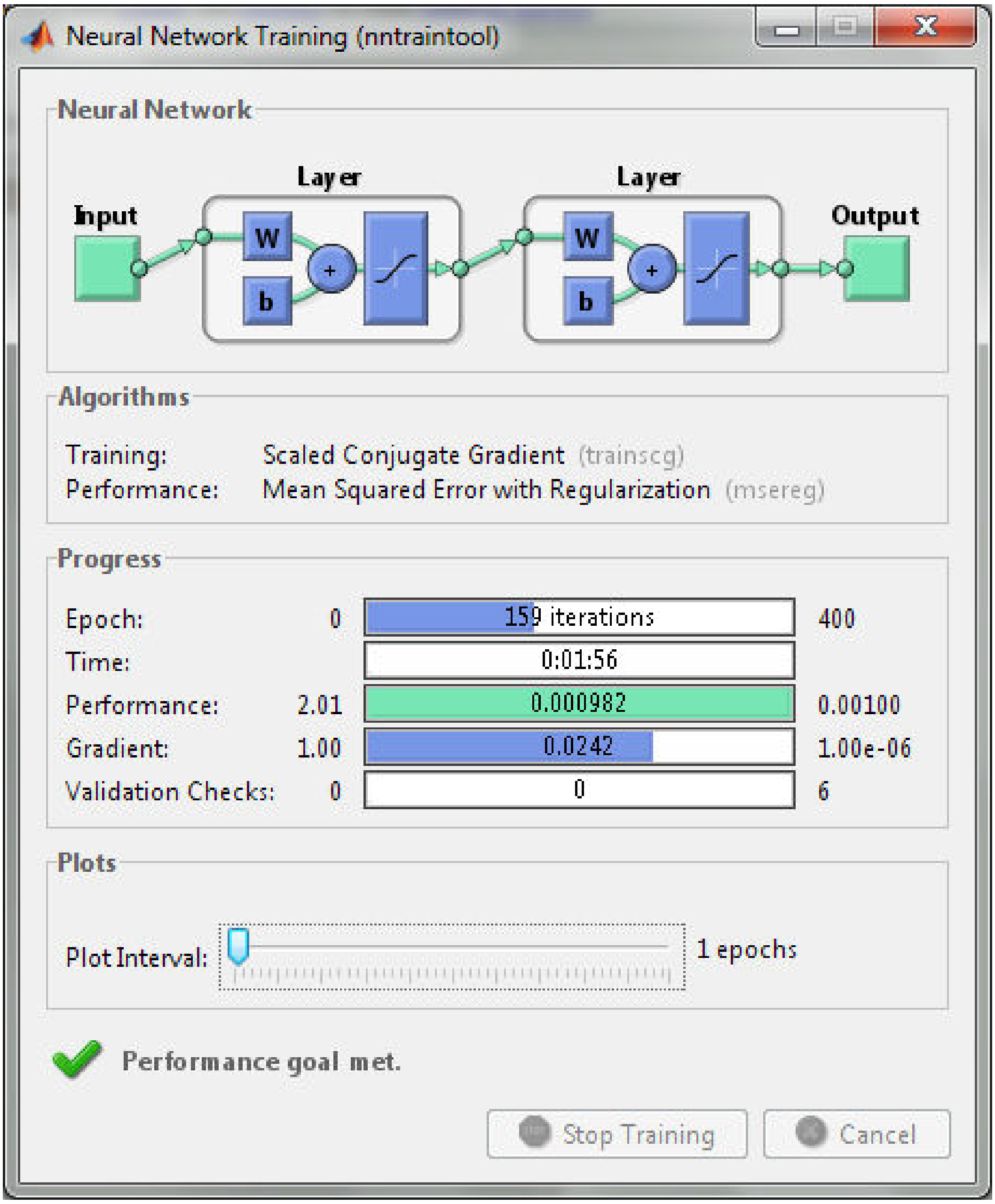


Fig. 16: Back propagation at training.
Activation function : scaled conjugate, 'trainscg'
Error rate measure : mean of squared error with regularization, 'msereg'

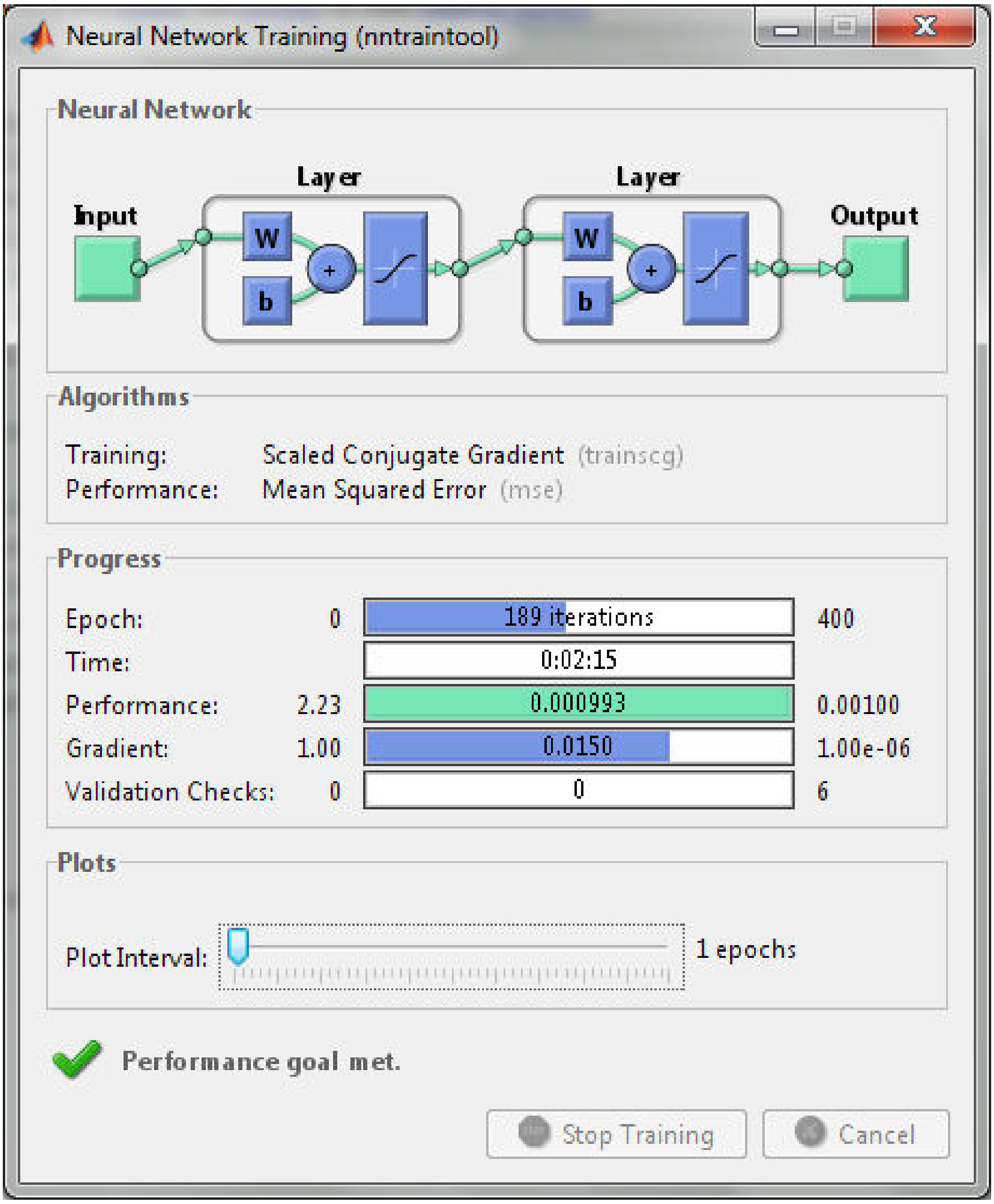


Fig. 17: Back propagation at training.
Activation function : scaled conjugate, 'trainscg'
Error rate measure : mean of squared error, 'mse'
Stopping criterion: performance goal met

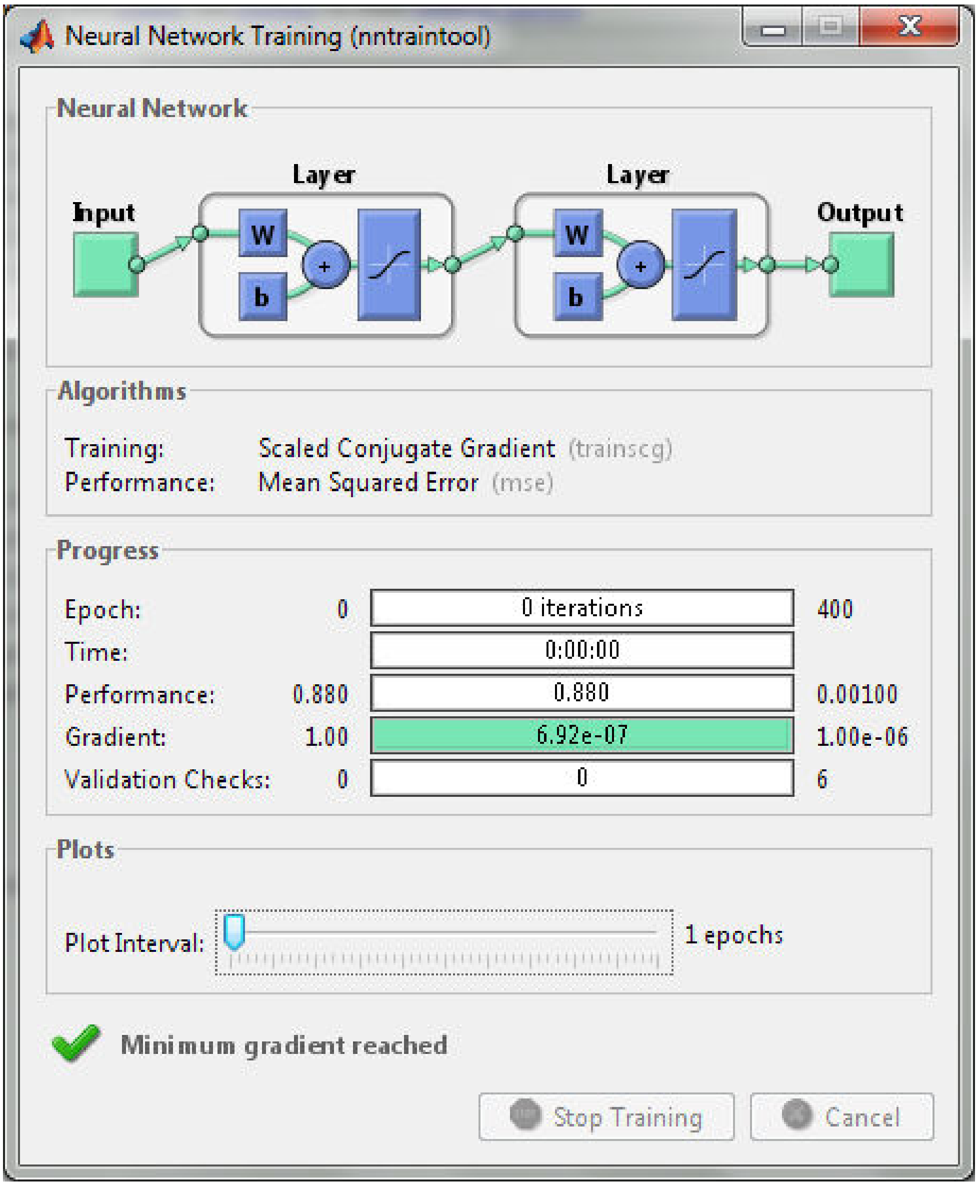


Fig. 18: Back propagation at training.
Activation function : scaled conjugate, 'trainscg'
Error rate measure : mean of squared error, 'mse'
Stopping criterion: minimum gradient reached

Table 1: The permanence of different biometrics over the time. The best permanence has most 0-symbols and the worst least [9].

Biometric Trait	*Permanence over time*
Fingerprint (Minutia)	000000
Signature (dynamic)	0000
Facial structure	00000
Iris pattern	000000000
Retina	00000000
Hand geometry	0000000
Finger geometry	0000000
Vein structure of the back of the hand	000000
Ear form	000000
Voice (Tone)	000
DNA	000000000
Odor	000000?
Keyboard strokes	0000
Comparison: Password	00000

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Table 2: Summary of comparison between Eigen-faces and Eigen-ears[3].

Experiment #	Face/Ear compared		Expected Result	Result
1	Same day, different expression	Same day, opposite ear	Greater variation in expressions than ears; ears perform better	Face performs better
2	Different day, similar expresion	Different day, same ear	Greater variation in expression across days; ears perform better	Face performs better
3	Differet day, different expression	Different day, opposite ear	Greater variation in face expression than ear; ears perform better	Face performs better

Table 3: Biometric suitability for authentication purposes. The best method has most 0-symbols and the worst least. This table is updated in 2000 [8].

Biometric Trait	Comfort	Accuracy	Availability	Costs
Fingerprint	0000000	000000●	0000	000
Signature (dynamic)	000	0000	00000	0000
Facial geometry	000000000	0000	0000000	00000
Iris	00000000	000000●00	00000000	00000000
Retina	000000	000000●0	00000	0000000
Hand geometry	000000	00000	000000	00000
Finger geometry	0000000	000	0000000	0000
Vein Structure of the back of the hand	000000	000000	000000	00000
Ear form	00000	0000	0000000	00000
Voice	0000	00	000	00
DNA	0	000000●	000000000	000000000
Odor	?	00	0000000	?
Keyboard strokes	0000	0	00	0
Comparison: Password	00000	00	00000000	0

green = best red = worst