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A reliable recognition System for Ear recognition

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Give this humble work

To my dear parents for their constant support, unconditional help, countless sacrifices, constant encouragement and patience with us since all years of .study

.That God gets them healthy and long life

For all my teachers during my years of study, which I .learned a lot

And my brothers (Younis, Mahmoud, Suhaib and Abdel Mohamed,Momen).

My sisters (Hajar, Fatima Zahra,Alaa, Amina)

Long live especially to (Ibtisam m, Mbarka A)

And to all my friends in all stages of my studies and

Any person who contributed to this work from near or far.

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General introduction

General introduction

Due to the current development of communications and technology and their journeys (physical, commercial, financial, etc.) we need to ascertain the identity of individuals. Because the most important risks come, try fraudsters to penetrate the current security systems. So researchers and developers want to invent sensitive and fast identification security devices.

The market of development and system identification has been shown to be effective against fraud.

There are moreover numerous offices where the passwords are noted in lists, what represents a dangerous fault in the IT security of the company because any confidentiality is then lost .de even, a badge or a key can be, stolen or copied by people ill-intentioned. The defect common to all the systems of authentification are that we identify an object (code, card) and not the person herself. In the face of the constraint of the authentification by "objects", the biometrics brings simplicity and a comfort to the users.

So we have to use biotechnologies to identify a person by creating a database so we chose the "ear" because it is a strong biological, and is more recognition of acceptance allows the use of Qmra ear.

Light and ear position are essential to getting the image.

This report deals with the subject of identifying the ear, in order to identify the identity of the person through his ears automatically, in this work we chose three techniques to extract the characteristics of the image of the ear.

So we have to use biotechnologies to identify a person by creating a database so we chose the "ear" because it is a strong biological, and is more recognition of acceptance allows the use of ear.

Thismemodeals with the subject of identifying the ear, in order to identify the identity of the person through his ears automatically, in this work we chose three techniques to extract the characteristics of the image of the ear.

The first method :Gray-Level Co-Occurrence Matrix(GLCM), is one of the most important ways to measure the texture of the ear, which analyzes the texture based on the following principles: variance, homogeneity, correlation and local homogeneity.

The second method : Local Binary Pattern(LBP) It is a mathematical method, which is the method of calculating the code for each pixel in the image and then calculate the graph of this image.

Module 1: Overview of biometric identification systems, how they are studied, how information is extracted, how they are studied, and why we chose the ear.

Module 2: All the algorithms that have been worked on in this note and there are many of them.

In the final unit: our work was discussed and studied the subject and we studied how this application works, which provides us with a study and assessment of the ear.

Chapter 1

OVERVIEW ONBIOMETRIC

INTRODUCTION TO BIOMETRICS

Reliable and highly accessible authentication and authentication techniques have become a must for human societies, with security vulnerabilities in mind. Biometrics have emerged to meet this need and have even evolved into a science that combines biotechnology and information technology to use physiological or behavioral characteristics in the human body To deal with the identification of individuals. It is applied to two main aspects of applications, identity verification and identification.

DEFENITION OF BIOMETRICS

The word biometrics comes from two Greek words meaning life scale ("vital" means life and "metric" means measurement). Is a branch of biology that uses measurement and statistical analysis to understand humans or animals.

1. When fingerprints and ear patterns are measured, this is an example of biometrics.
2. When studying human genetics patterns by looking at statistics on population growth, this is an example of biometrics.

This section of biology, which deals with its data statistically, is mathematical analysis. Measurement and scientific analysis of biological data, as in the identification of individuals or in forensic medicine.

In validation, biometrics indicate the measurement of the physiological and behavioral characteristics used to identify computer users. Physiological characteristics usually include face, fingerprints and DNA. Behavioral characteristics typically include a user's digital signature, voice or walk. Although many methods are involved in biometrics.]

Biometric modalities

It is essential to be familiar with the characteristics of biometric systems in order to better understand how to think objectively about each type and make rational decisions about purchasing and using the technology.Ideally, the biometric characteristics used should satisfy the following properties:

- ***Robustness:*** Over time, the characteristic should not change (Permanence), and thus have low intra-class variability.
- ***Distinctiveness***: Over the population, a great variation of the characteristic shouldexist (Uniqueness), and thus have large inter-class variability.
- ***Availability***: Ideally, the whole population should possess the characteristic (Universality).
- ***Accessibility***: The characteristic should be easy to acquire (Collectability).

Given the multitude of characteristics that is coupled to a human being, we need some way of classifying the different biometric identifiers, also called the biometric ***modalities***. A first step is to group them as either behavioral or physiological. Behavioral identifiersare measurable traits that are acquired over time. The traits can then be used for authentication of a person's identity by using pattern recognition techniques. Behavioral identifiers include for example signature recognition, voice recognition and keystroke dynamics. Physiological identifiersare something you *are* rather than something you do or know. There are many types ofphysiological identifiers, including fingerprint, handprint, iris and retina, face, DNA, EEG and many more, as shown in [2][3].

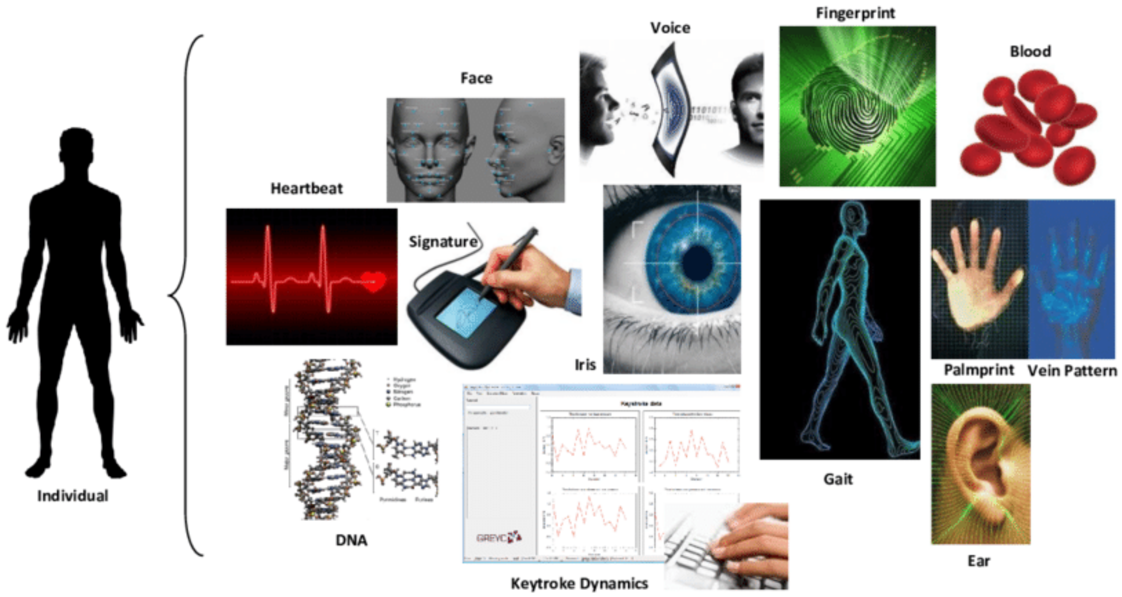

Figure 1:Different physiological and/or behavioral biometric characteristics.

1-Physiologicaltraits

1-1-Iris recognition

The iris recognition system is an advanced field and is a major development using the human iris to identify. By calculating the iris feature, it is possible to identify each individual population [4][5].

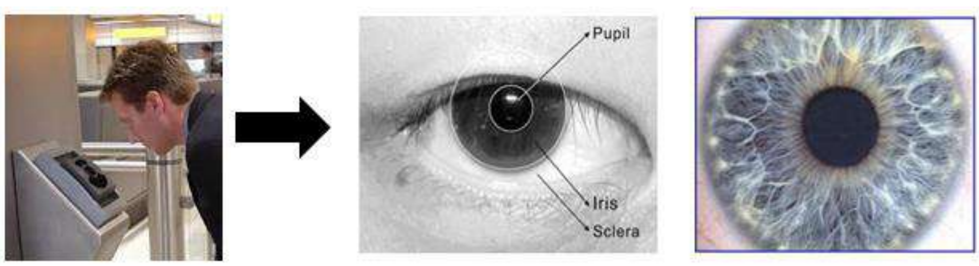

Figure2:Iris

1.2. Palm printrecognition

Palm leaf recognition is a biometric technique that recognizes a person based on the pattern of palm printing. Hand printing is a trusted human identifier because print patterns are not repeated in other people, even in monogamous twins[5].

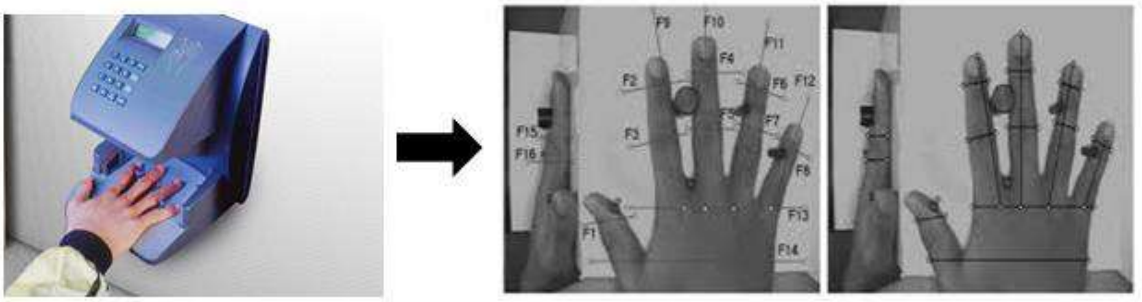

Figure 2:Plam print

1.3. Veinrecognition

Finger-vein authentication is one of the newer biometric modalities. It captures images of the unique vein patterns inside the finger by passing near-infrared light through it and recording the effect via a sensor[6].

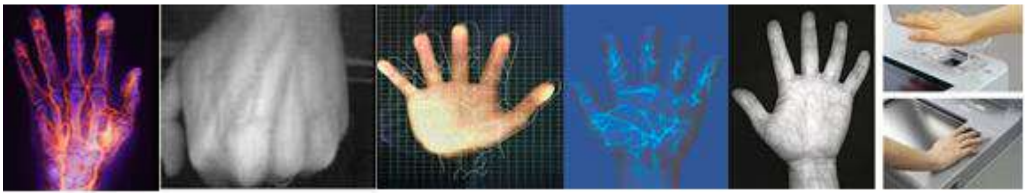

Figure 3:vein recognition

1.4.Finger print recognition

Since the introduction of fingerprints (cameras or markers) for the first time as evidence to convict the suspect in 1893, fingerprint recognition, being the main biological identifier used, shows the hills on the skin unique patterns of our fingertips in our fingerprints[6].

Figure 4:Fingerprint

1.5. Facial recognition

Face recognition involves taking many photos or facial images and extracting unique facial features as well as distances from or between the ears, eyes, cheeks, nose and mouth[8].

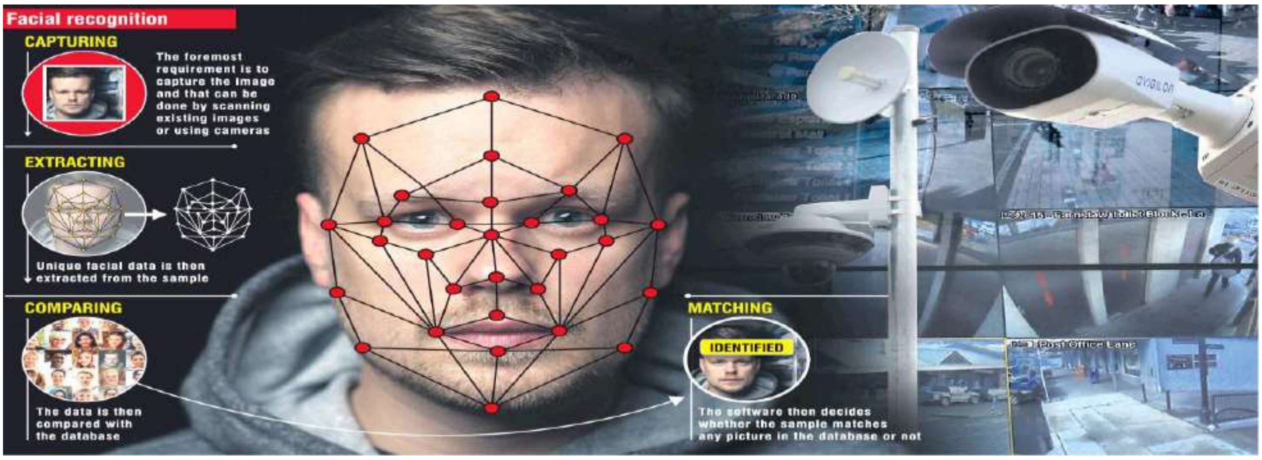

FIGURE 5:FACIAL RECOGNITION

1.6. Retinarecognition

Retinal-scan modality makes use of the retina, which is the surface on the back of the eye that processes light entering through the pupil. The principle behind this modality is that the blood vesselsinthe retina provide a unique pattern, which may be used as a tamper-proof personal identifier[6].

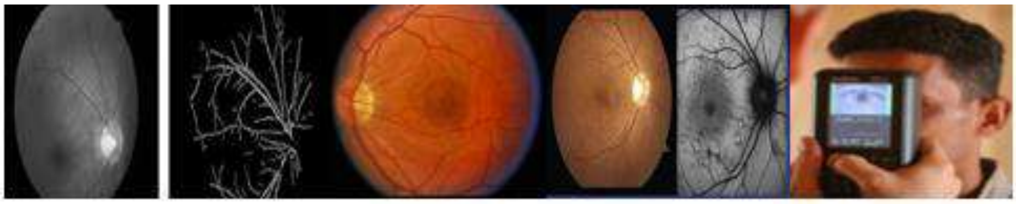

Figure 6:Retina recognition

1.7. DNArecognition

Deoxyribonucleicacid (DNA) is the structure that defines who we are physically and intellectually, unless an individual is an identical twin, it is not likely that any other person will have the same exact set of genes (Philipkoski, K., 2004).

DNA can be collected from any number of sources: blood, hair,fingernails, mouth swabs, blood stains, saliva, straws, and any number of other sources that has been attached to the body at some time. DNA matching has become a popular use in criminal trials[6].

Figure 7: DNA recognition

1.8. FKPrecognition

Finger-Knuckle-Print (FKP) is one of the emerging biometric traits. The region of interest is the area where the maximum information is centered, for a finger knuckle it is the area surrounding the knuckle region[6].

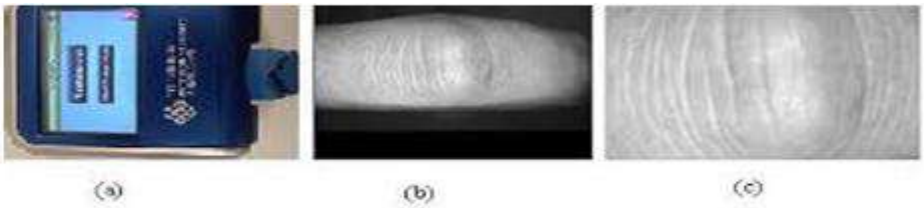

Figure 8:FKP recognition

1.9. Tongue printrecognition

The tongue is a unique organ in that it can be stuck out of mouth for inspection, and yet it is otherwise well protected in the mouth and is difficult to forge. The tongue also presents both geometric shape information and physiological texture information which are potentially useful in identity verification applications[6].

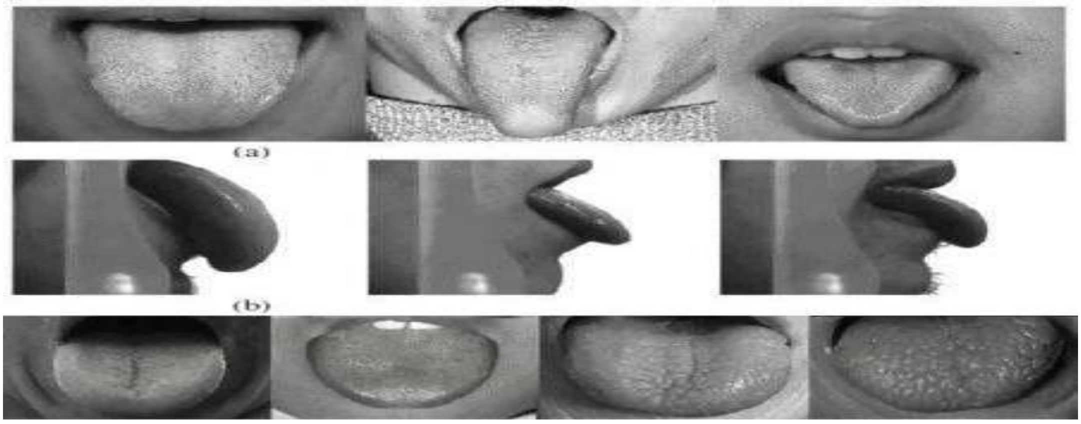

Figure 9:Tongue print recognition

1.10. Ear shaperecognition

Ear recognition may be done using a digital image, a thermo-graphic image or an ear print. An ear print can be taken by pressing the ear against theflat paper[6].

Figure 10:Ear Shape

2. Behavioral

2.1. Gaitrecognition

Human gait recognition works from the observation that an individual’s walking style is unique and can be used for human identification. So as to recognize individual’s walking characteristics, gait recognition includes visual cue extraction as well as classification[6].

Figur**e12**:gait recognition

2.2. Voicerecognition

Voice recognition is the process of automatically recognizing who is speaking on the basis of individual information included in speech waves[6].

Figure13:Voice recognition

2.3. Signaturerecognition

Each person has a unique style of handwriting, and no two signatures of different persons are identical. However, the variations of a typical signature also depend upon the physicaland emotional state of a person[6].

Figure14:Signature recognition

2.4. Keystrokesrecognition

Keystroke Dynamicsis one of the famous biometric technologies, which identifies the authenticity of a user whenthe user is working via a keyboard. The authentication process is done by observing thevariation in the typing pattern of the user. A comprehensive study of the existing keystrokedynamics methods, metrics, and different approaches are presented[6].

Figure15:Keystroks recognition

2.5. Electrocardiogramrecognition

The human heartbeat can be used for identity recognition. Existing solutions for biometric recognition from electrocardiogram (ECG) signals are based on temporal and amplitude distances between detected fiducially points [7].

Figure16:Electrocardiogramrecobnition

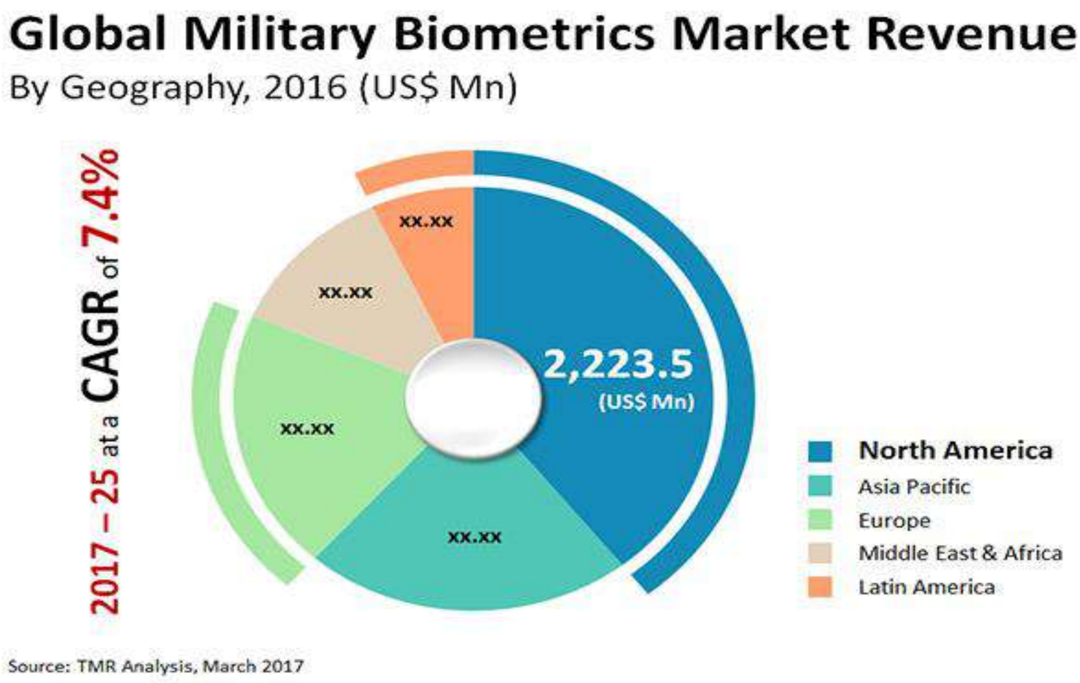

Figure17:Biometrics market share by system type .based on revenue

(**Source**: ABI Research 2016)

3.Biometric system

Although the various biometric technologies vary in what and how they scan, the principle of operation is very similar.It consists predefined steps as well as we must know some basic terms related toabiometric system as enrollment, biometric data, presentation, template, feature extraction, matching,Decision.

3.1.Enrollment or Registration : The process, by which a user's biometric data is initially obtain,processed and stored in the form of a template for ongoing use in a biometric system. It is called enrollment or registration process. This template will be used for further process as authentication.

3.2.Biometric Data: The data presented by the user during registration is called unprocessed image data, which is also referred as raw biometric data or biometric sample. Raw biometric data cannot be used to perform biometric matches so it is used to generate biometric template with the help of feature extraction process.

3.3.Presentation: The process by which user presents his/her biometric data to the acquisition devices, thehardware which is used to collect data. For example, placing a finger on a plate at finger reader device.

3.4.Template: A mathematical representation of raw biometric data, which is obtained after applying a numberof feature extraction algorithms. A template size can vary in size from afew bytes for hand geometry to severalthousand bytes for facial recognition. The template created at the time of registration is called storedtemplate and at the time of authentication is calleda live template.

3.5.Feature Extraction: The process of locating and encoding distinctive characteristics from biometric data inorder to generate a template is called feature extraction. Feature extraction takes place during enrollmentand verification, any time a template is created.

3.6.Matching: A process wherethestored template is matched with thelive template at the time of verification andwe obtained a score, on the basis of this score we conclude that a user is authenticated human or not.

3.7.Decision-making: The user's identity is either established or a claimed identity is accepted or rejected. This is done based on the results of the matching modules.

INTRODUCTION TO EAR

Try a simple experiment, try to visualize what your ears look like. You were not able to? Well, then try to describe the ears of someone you see everyday. You will find that even if you are looking directly at someone's ears, they are still difficult to describe. We simply do not have the vocabulary for it; our everyday language provides only a few adjectives which can be applied to ears, all of which are generic adjectives like large or floppy and not ones which are solely1 used to describe ears. On the other hand, we are all capable of describing the faces of even briefly glimpsed strangers with significant detail to allow police artists to reconstruct remarkable resemblances of them. Even though we apparently lack the means to recognize one another from our ears, we will see that the rich structure of the ear is unique and that it can be used as an effective biometric for passive identification

4.EAR

Proposing the ear as the basis for a new class of biometrics, we need to show that it is viable (i.e., unique to each individual, and comparable over time). we can not show that each of us has a unique pair of ears. Instead, we will assert that this is probable and give supporting evidence by examining two studies from Iannarelli . The first study compared over 10,000 ears drawn from a randomly selected sample in California, and the second study examined fraternal and identical twins, in which physiological features are known to be similar. The evidence from these studies supports the hypothesis that the ear contains unique physiological features, since in both studies all examined ears were found to be unique though identical twins were found to have similar, but not identical, ear structures especially in the Concha and lobe areas. Having shown uniqueness, it remains to ascertain if the ear provides biometrics which are comparable over time.

It is obvious that the structure of the ear does not change radically over time. The medical literature reports that ear growth after the first four months of birth is proportional. It turns out that even though ear growth is proportional, gravity can cause the ear to undergo stretching in the vertical direction. The effect of this stretching is most pronounced in the lobe of the ear, and measurements show that the change is non-linear. The rate of stretching is approximately five times greater than normal during the period from four months to the age of eight, after which it is constant until around 70 when it again increases. We have shown that biometrics based upon the ear are viable in that the ear anatomy is probably unique to each individual and that features based upon measurements of that anatomy are comparable over time. Given that they are viable, identification by ear biometrics is promising because it is passive like face recognition, but instead of the difficult to extract face biometrics, robust and simply extracted biometrics like those in fingerprints can be used[8].

.Figure19: Ear structure

4.1.Why The Ear ?

Uniqueness of ear

Two studies were done to examine the uniqueness of humanear. The first study is made by Alfred Iannarelli at 1989,when he gathered up over 10,000 ears drawn from a randomly selected sample in California and found that they all were different , and the second study examined fraternal and identical twins, in which physiological features are known to be similar. The evidence from these studies supports the hypothesis that the ear contains unique physiological features, since in both studies all examined ears were found to be unique though identical twins were found to have similar, but not identical .There are also persons in crime laboratories that assume that the human external ear characteristics are unique to each individual[9].

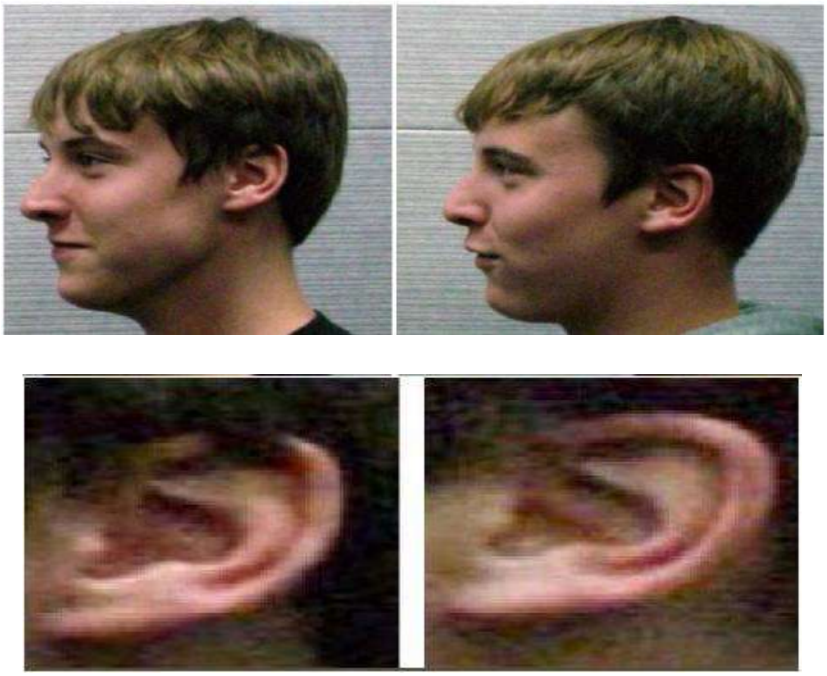

Figure 11:Identical twins have similar ears but not identical.

4.2.Methods of ear acquisition

There are at least four methods for ear acquisition:

(i) Taking a *photo* of an ear.

(ii) Taking "*earmarks*" by pushing ear against a flat glass.

(iii) Taking *thermo gram pictures* of the ear.

(iv) Taking a *range image* of the ear.

The most interesting parts of the ear are the outer ear and earlope, but the whole ear structure and shape is used. Takingphoto of the ear is the most commonly used method inresearch. The photo is taken and combined with previoustaken photos for identifying a person. The earmarksareusedmainly in crime solving

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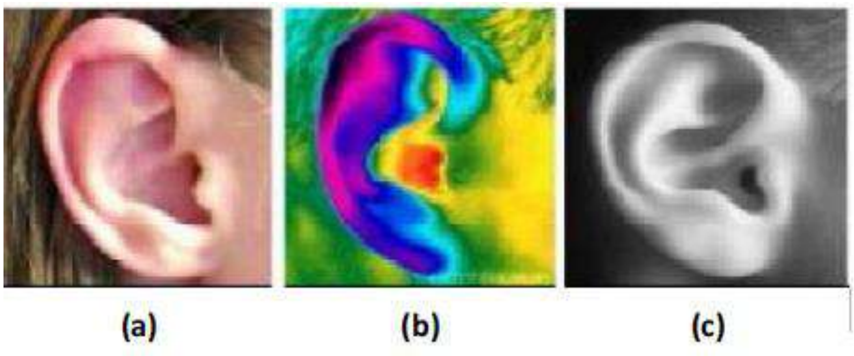


Figure 12:Different methods for ear acquisition, (a) photo of an ear, (b)

4.3.Advantages of ear

Identification by ear biometrics is promising because it is passive like face recognition, but instead of the challenges of face biometrics ears are more consistent as far as variability due to expression, orientation of the face, changing lightning and effect of aging, cosmetics, hair styles, and the growth of facial hair as well. The ear
is a unique feature of human beings. Even the ears of “identical twins” differ in some respects as mentioned before [9] [10].

Conclusion

Through this chapter, we presented the concept of biometrics, engineering and its various applications, and the main units of biometric systems and how to measure their performance We also discussed the study of permission and why it is authorized with all the interpretations reached by modern science .

Chapter 2

Used algorithms

Chapter 2 : Used algorithms
INTRODUCTION

In this article , we will need to identify and address a set of algorithms that we need especially in this note, their knowledge and areas of use. There are two types of algorithms, some of which are used to identify, and some are used for classification.

1-K-Nearest Neighbors(KNN)

In this article, we will talk about another widely used classification technique called K-nearest neighbors (KNN) . Our focus will be primarily on how does the algorithm work and how does the input parameter effect the output/prediction[10].

1.1.When do we use KNN algorithm?

KNN can be used for both classification and regression predictive problems. However, it is more widely used in classification problems in the industry. To evaluate any technique we generally look at 3 important aspects:

1. Ease to interpret output
2. Calculation time
3. Predictive Power

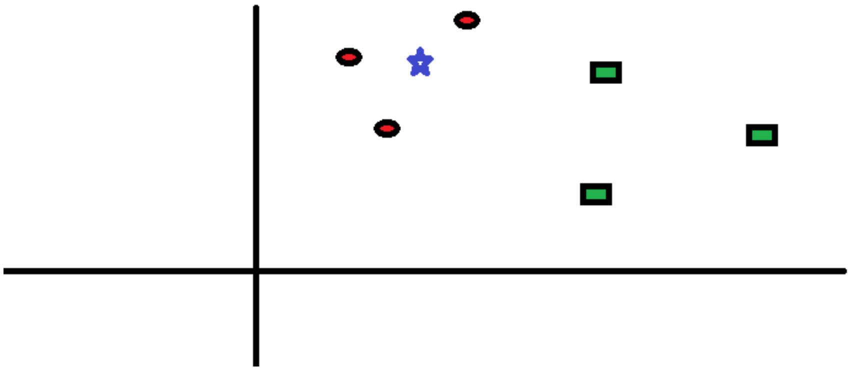
Let us take a few examples to place KNN in the scale :

	Logistic Regression	CART	Random Forest	KNN
1. Ease to interpret output	2	3	1	3
2. Calculation time	3	2	1	3
3. Predictive Power	2	2	3	2

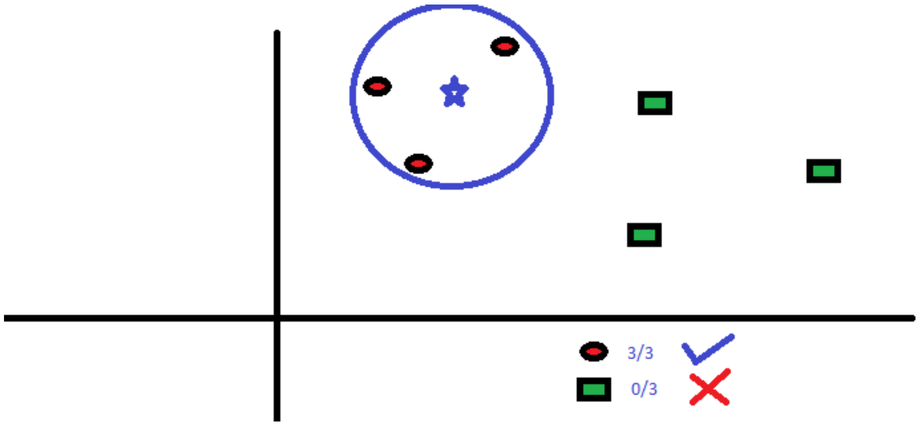
KNN algorithm fairs across all parameters of considerations. It is commonly used for its easy of interpretation and low calculation time.

1.2.How does the KNN algorithm work?

Let's take a simple case to understand this algorithm. Following is a spread of red circles (RC) and green squares (GS) :



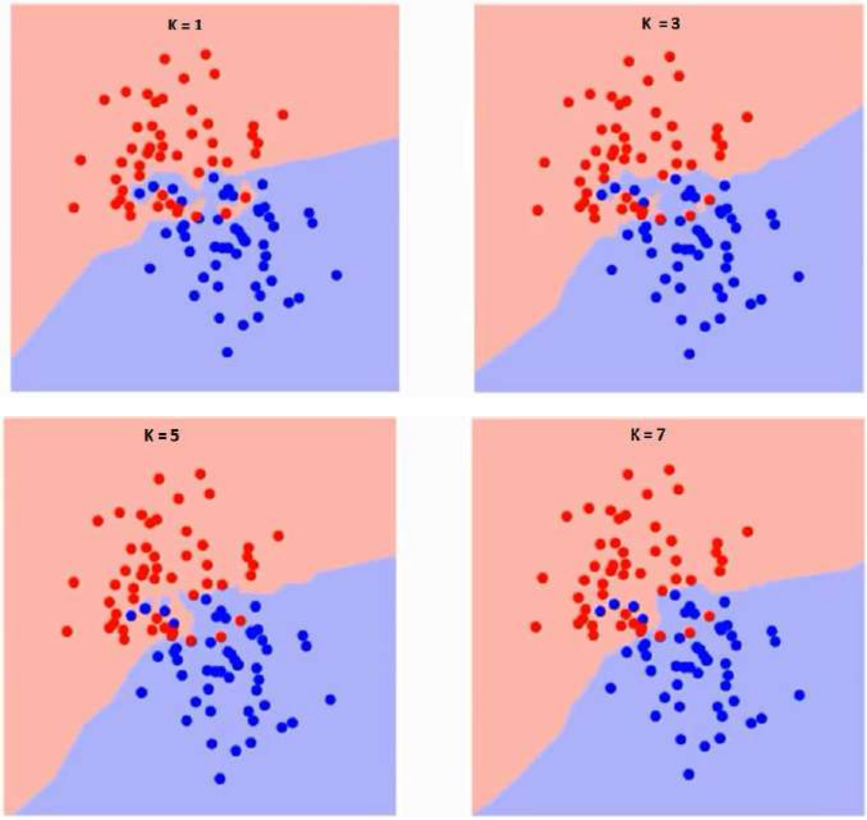
You intend to find out the class of the blue star (BS) . BS can either be RC or GS and nothing else. The “K” is KNN algorithm is the nearest neighbors we wish to take vote from. Let’s say K = 3. Hence, we will now make a circle with BS as center just as big as to enclose only three datapoints on the plane. Refer to followingdiagram for more details:



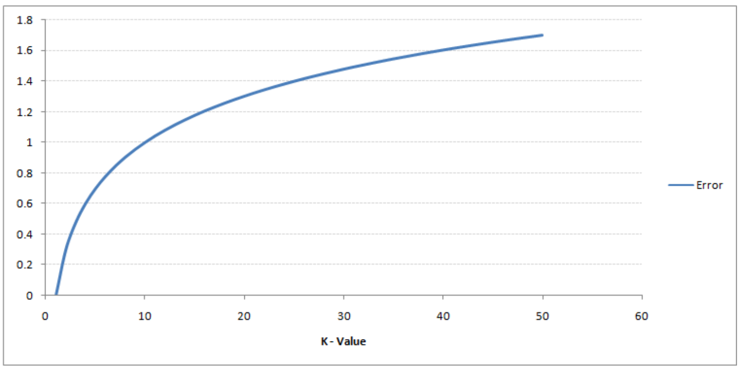
The three closest points to BS is all RC. Hence, with good confidence level we can say that the BS should belong to the class RC. Here, the choice became very obvious as all three votes from the closest neighbor went to RC. The choice of the parameter K is very crucial in this algorithm. Next we will understand what are the factors to be considered to conclude the best K[22].

1.3.How do we choose the factor K?

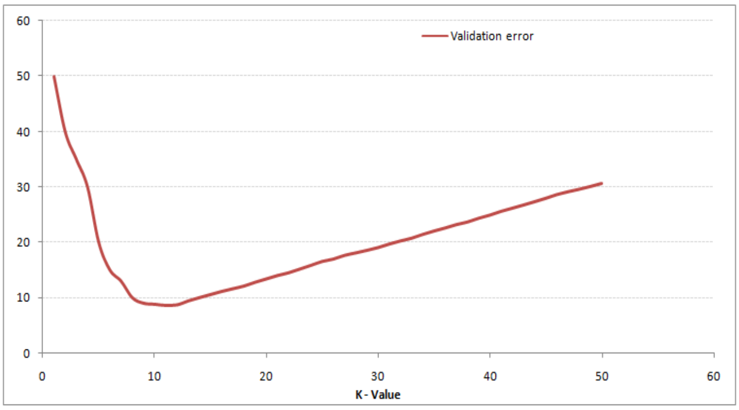
First let us try to understand what exactly does K influence in the algorithm. If we see the last example, given that all the 6 training observation remain constant, with a given K value we can make boundaries of each class. These boundaries will segregate RC from GS. The same way, let’s try to see the effect of value “K” on the class boundaries. Following are the different boundaries separating the two classes with different values of K.



If you watch carefully, you can see that the boundary becomes smoother with increasing value of K. With K increasing to infinity it finally becomes all blue or all red depending on the total majority. The training error rate and the validation error rate are two parameters we need to access on different K-value. Following is the curve for the training error rate with varying value of K :



As you can see, the error rate at K=1 is always zero for the training sample. This is because the closest point to any training data point is itself.Hence the prediction is always accurate with K=1. If validation error curve would have been similar, our choice of K would have been 1. Following is the validation error curve with varying value of K:



This makes the story more clear. At K=1, we were overfitting the boundaries. Hence, error rate initially decreases and reaches a minima. After the minima point, it then increase with increasing K. To get the optimal value of K, you can segregate the training and validation from the initial dataset. Now plot the validation error curve to get the optimal value of K. This value of K should be used for all predictions.

2-Artificial Neural Networks (ANN).

In this article, we will talk about another widely used classification technique called artificial neural networks. Our focus will be mainly on how the algorithm works[23].

2.1.What are Artificial Neural Networks?

An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes - or learns, in a sense - based on that input and output.

2.2.Artificial Neurons and How They Work

The fundamental processing element of a neural network is a neuron. This building block of human awareness encompasses a few general capabilities. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then outputs the final result. shows the relationship of these four parts.

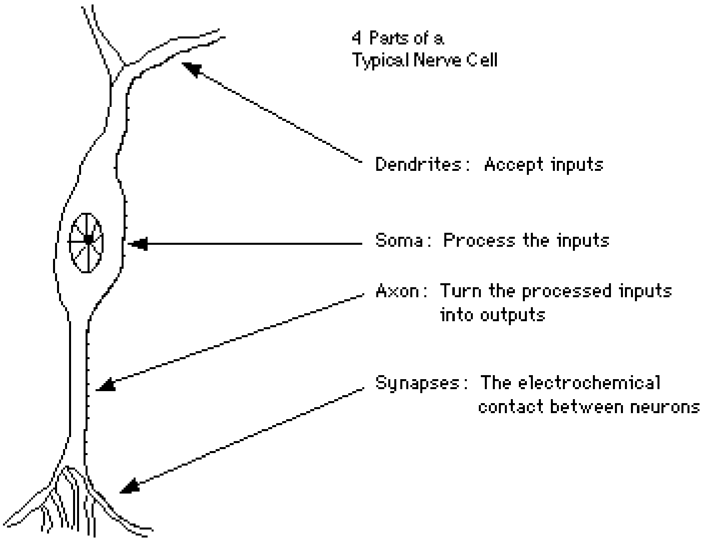


Figure 13:Simple Neuron.

Within humans there are many variations on this basic type of neuron, further complicating man's attempts at electrically replicating the process of thinking. Yet, all natural neurons have the same four basic components. These components are known by their biological names - dendrites, soma, axon, and synapses. Dendrites are hair-like extensions of the soma which act like input channels. These input channels receive their input through the synapses of other neurons. The soma then processes these incoming signals over time. The soma then turns that processed value into an output which is sent out to other neurons through the axon and the synapses.

Recent experimental data has provided further evidence that biological neurons are structurally more complex than the simplistic explanation above. They are significantly more complex than the existing artificial neurons that are built into today's artificial neural networks. As biology provides a better understanding of neurons, and as technology advances, network designers can continue to improve their systems by building upon man's understanding of the biological brain.

But currently, the goal of artificial neural networks is not the grandiose recreation of the brain. On the contrary, neural network researchers are seeking an understanding of nature's capabilities for which people can engineer solutions to problems that have not been solved by traditional computing.

To do this, the basic unit of neural networks, the artificial neurons, simulate the four basic functions of natural neurons. Figure shows a fundamentalrepresentation of an artificialneuron[11].

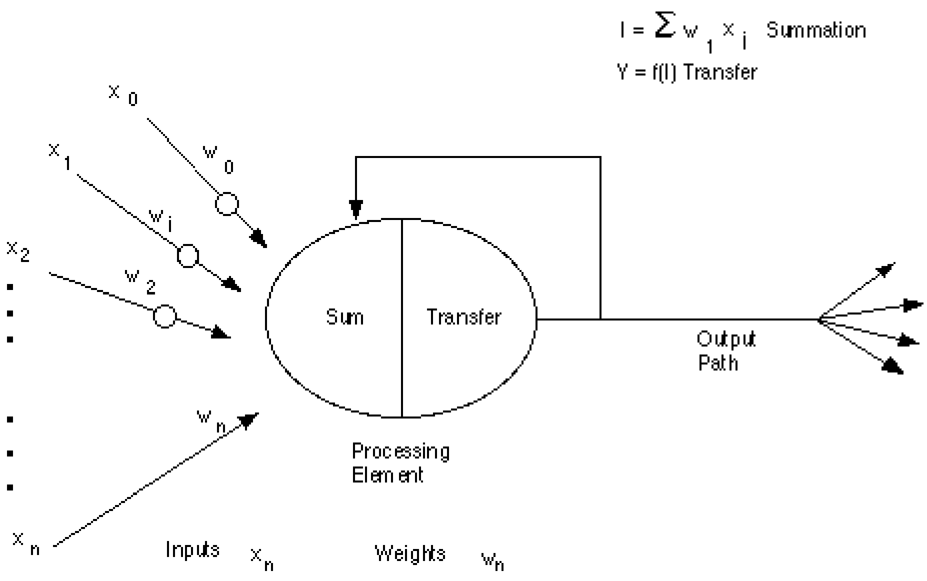


Figure 14: Basic Artificial Neuron.

In Figure , various inputs to the network are represented by the mathematical symbol, x(n). Each of these inputs are multiplied by a connection weight. These weights are represented by w(n). In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then output. This process lends itself to physical implementation on a large scale in a small package. This electronic implementation is still possible with other network structures which utilize different summing functions as well as different transfer functions.

Some applications require "black and white," or binary, answers. These applications include the recognition of text, the identification of speech, and the image deciphering of scenes. These applications are required to turn real-world inputs into discrete values. These potential values are limited to some known set, like the ASCII characters or the most common 50,000 English words. Because of this limitation of output options, these applications don't always utilize networks composed of neurons that simply sum up, and thereby smooth, inputs. These networks may utilize the binary properties of ORing and ANDing of inputs. These functions, and many others, can be built into the summation and transfer functions of a network.

Other networks work on problems where the resolutions are not just one of several known values. These networks need to be capable of an infinite number of responses. Applications of this type include the "intelligence" behind robotic movements. This "intelligence" processes inputs and then creates outputs which actually cause some device to move. That movement can span an infinite number of very precise motions. These networks do indeed want to smooth their inputs which, due to limitations of sensors, comes in non-continuous bursts, say thirty times a second. To do that, they might accept these inputs, sum that data, and then produce an output by, for example, applying a hyperbolic tangent as a transfer function. In this manner, output values from the network are continuous and satisfy more real world interfaces.

Other applications might simply sum and compare to a threshold, thereby producing one of two possible outputs, a zero or a one. Other functions scale the outputs to match the application, such as the values minus one and one. Some functions even integrate the input data over time, creating time-dependent networks.

2.3.Artificial Network Operations

The other part of the "art" of using neural networks revolve around the myriad of ways these individual neurons can be clustered together. This clustering occurs in the human mind in such a way that information can be processed in a dynamic, interactive, and self-organizing way. Biologically, neural networks are constructed in a three-dimensional world from microscopic components. These neurons seem capable of nearly unrestricted interconnections. That is not true of any proposed, or existing, man-made network. Integrated circuits, using current technology, are two-dimensional devices with a limited number of layers for interconnection. This physical reality restrains the types, and scope, of artificial neural networks that can be implemented in silicon.

Currently, neural networks are the simple clustering of the primitive artificial neurons. This clustering occurs by creating layers which are then connected to one another. How these layers connect is the other part of the "art" of engineering networks to resolve real world problems[12].

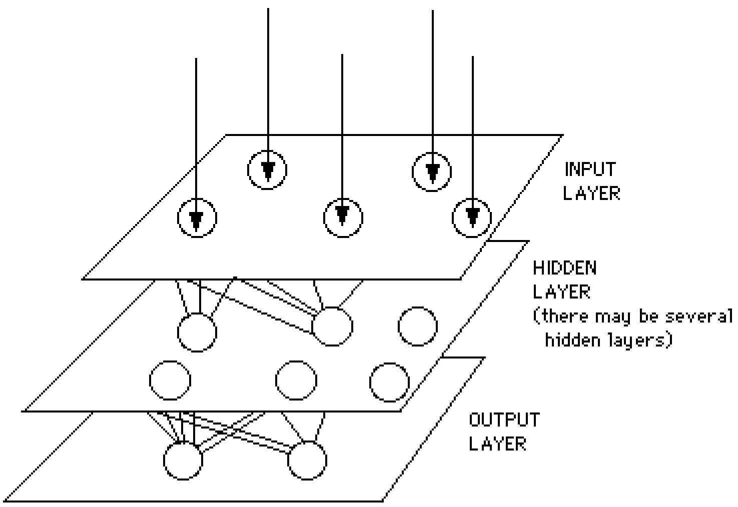


Figure 15: Simple Neural Network Diagram.

Basically, all artificial neural networks have a similar structure or topology as shown in Figure. In that structure some of the neurons interfaces to the real world to receive its inputs. Other neurons provide the real world with the network's outputs. This output might be the particular character that the network thinks that it has scanned or the particular image it thinks is being viewed. All the rest of the neurons are hidden from view.

But a neural network is more than a bunch of neurons. Some early researchers tried to simply connect neurons in a random manner, without much success. Now, it is known that even the brains of snails are structured devices. One of the easiest ways to design a structure is to create layers of elements. It is the grouping of these neurons into layers, the connections between these layers, and the summation and transfer functions that comprises a functioning neural network. The general terms used to describe these characteristics are common to all networks.

Although there are useful networks which contain only one layer, or even one element, most applications require networks that contain at least the three normal types of layers - input, hidden, and output. The layer of input neurons receive the data either from input files or directly from electronic sensors in real-time applications. The output layer sends information directly to the outside world, to a secondary computer process, or to other devices such as a mechanical control system. Between these two layers can be many hidden layers. These internal layers contain many of the neurons in various interconnected structures. The inputs and outputs of each of these hidden neurons simply go to other neurons.

In most networks each neuron in a hidden layer receives the signals from all of the neurons in a layer above it, typically an input layer. After a neuron performs its function it passes its output to all of the neurons in the layer below it, providing a feedforward path to the output. (Note: in section 5 the drawings are reversed, inputs come into the bottom and outputs come out the top.)

These lines of communication from one neuron to another are important aspects of neural networks. They are the glue to the system. They are the connections which provide a variable strength to an input. There are two types of these connections. One causes the summing mechanism of the next neuron to add while the other causes it to subtract. In more human terms one excites while the other inhibits.

Some networks want a neuron to inhibit the other neurons in the same layer. This is called lateral inhibition. The most common use of this is in the output layer. For example in text recognition if the probability of a character being a "P" is .85 and the probability of the character being an "F" is .65, the network wants to choose the highest probability and inhibit all the others. It can do that with lateral inhibition. This concept is also called competition. Another type of connection is feedback. This is where the output of one layer routes back to a previous layer. An example of thisisshown in Figure

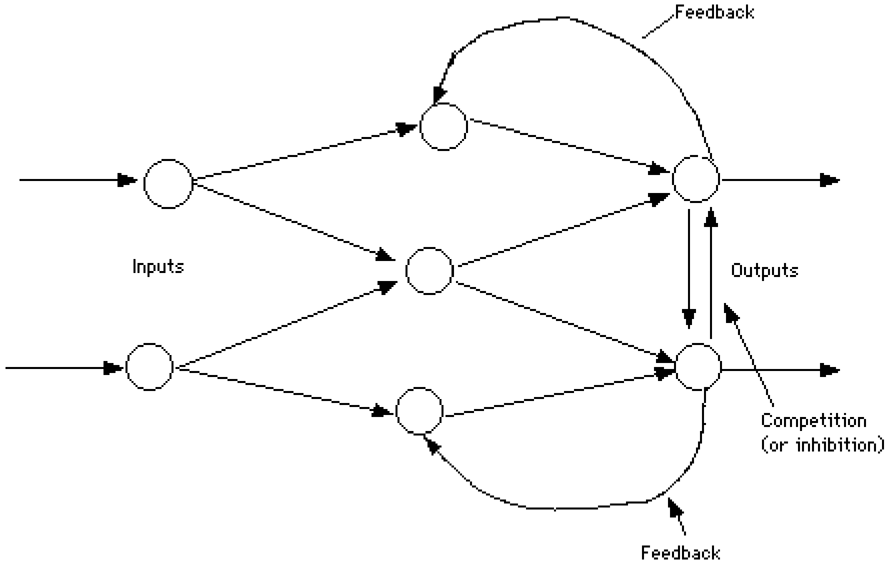


Figure25:Simple Network with Feedback and Competition..

The way that the neurons are connected to each other has a significant impacton the operation of the network. In the larger, more professional softwaredevelopment packages the user is allowed to add, delete, and control theseconnections at will. By "tweaking" parameters these connections can be made toeither excite or inhibit [13].

3-Local Binary Pattern(LBP)

Local Binary pattern is a type of visual descriptor used for classification in computer vision. LBP is the particular case of texture spectrum model.

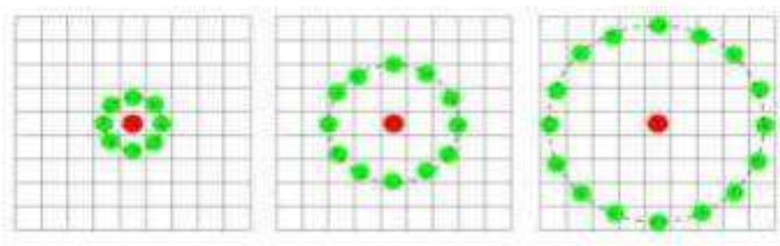


Figure 16:Local Binary PatterAlgorithm**.**

The Local Binary Pattern LBP feature version can be created in the simplest form in the following manner.

- Divide the examined window into cell.

- For each pixel in a cell, compare the pixel to each of its 8 neighbour, Follow the pixel along a circle.
- Where the center pixel's values is greater than the neighbour's value, write 0 otherwise write 1.
- Compute the histogram, over the cell as such the frequency of each number occur-ring.
- This gives a 8-digit binary number.
- Optionally normalize the histogram

To understand more on Local Binary Pattern Algorithm consider the following example. The original LBP operator labels the pixels of an image by keeping the 3x3 neighbourhood or it can be also said as a Matrix. Each pixel have value which can be vary depending upon the image and pixel quality. If a middle pixel ”168” is chosen which have eight neighbour[13].

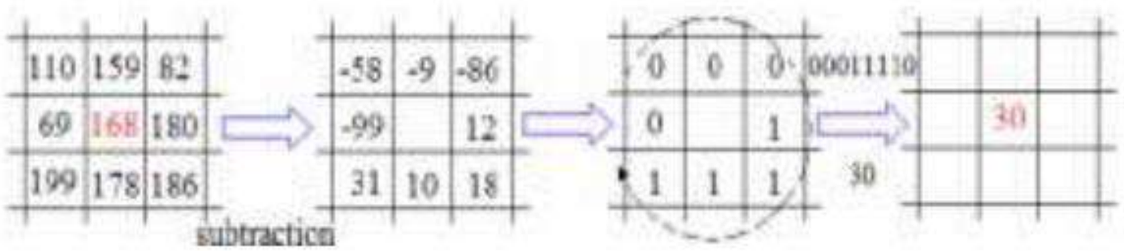


Figure27:Example of Basic Local Binary Pattern Operator.

Subtract these neighbour values with 168 if the value is less than zero put it as zero and if the value is more than zero put it as one.Starting from the top-left corner pixel you will get the binary number as 00011110 i.e. 30 in decimal system. The overallresulting LBP canbeexpressed as.

$$LBP(Xc,Yc) = \sum_{n=0}^{7} s(in - ic)2^{n}$$

where n runs over the 8 neighbour of the center pixel, ic and in are gray-level values of the central pixel. and this

$$s(x) = \begin{cases} 1, & if x \geq 0 \\ 0, & else \end{cases}$$

function can be defined as. But there are some limitation to basic LBP operator that its small 3x3 matrix method can not capture the dominant features with large scale structure. As a result, to deal with the texture at different scales, the operator can be extended to use neighbourhoods of different size.

3.1.Face Description using Local Binary Pattern

In the LBP approach for texture classification, the occurrences of the LBP codes in an image are collected into a histogram. The classification is then performed by computing simple histogram similarities. However, considering a similar approach for facial image representation results in a loss of spatial information and therefore one should codify the texture information while retaining also their locations. One way to achieve this goal is to use the LBP texture descriptors to build several local descriptions of the face and combine them into a global description. Such local descriptions have been gaining interest lately which is understandable given the limitations of the holistic representations. These local feature based methods are more robust against variations in pose or illumination than holistic methods. The facial image is divided into local regions and LBP texture descriptors are extracted from each region independently. The descriptors are then concatenated to form a global description of the face .

This histogram effectively has a description of the face on three different levels of locality: the LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level and the regional histograms are concatenated to build a global description of the face. It should be noted that when using the histogram based methods the regions do not need to be rectangular. Neither do they need to be of the same size or shape, and they do not necessarily have to cover the whole image. It is also possible to have partially overlapping regions[14].

4-Gray-Level Co-Occurrence Matrix (GLCM)

The texture filter functions provide a statistical view of texture based on the image histogram. These functions can provide useful information about the texture of an image but cannot provide information about shape, i.e., the spatial relationships of pixels in an image.

Another statistical method that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The toolbox provides functions to create a GLCM and derive statistical measurements from it.

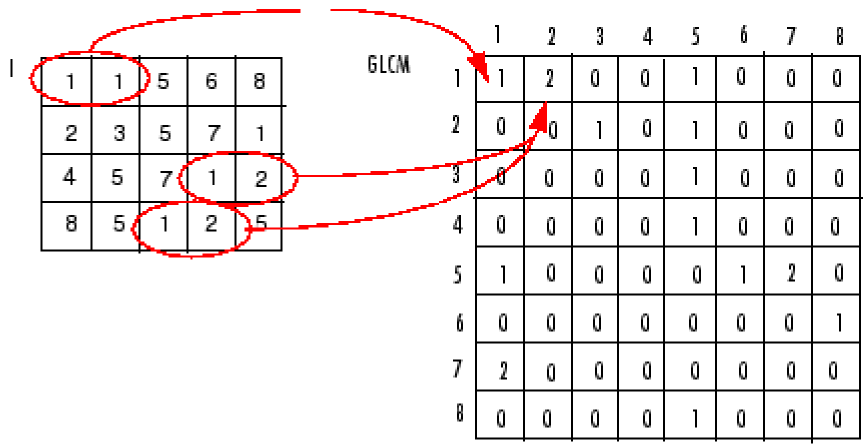
4.1.What is GREY level co occurrence matrix?

To create a GLCM, use the graycomatrix function. The function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value *i* occurs in a specific spatial relationship to a pixel with the value *j*. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (*i*,*j*) in the resultant glcm is simply the sum of the number of times that the pixel with value *i* occurred in the specified spatial relationship to a pixel with value *j* in the input image.

The number of gray levels in the image determines the size of the GLCM. By default, graycomatrix uses scaling to reduce the number of intensity values in an image to eight, but you can use the NumLevels and the GrayLimits parameters to control this scaling of gray levels. See the graycomatrix reference page for more information.

The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. You can also derive several statistical measures from the GLCM. See Derive Statistics from GLCM and Plot Correlation for more information.

To illustrate, the following figure shows how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. glcm(1,2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. graycomatrix continues processing the input image, scanning the image for other pixel pairs (*i*,*j*) and recording the sums in the corresponding elements of the GLCM.



4.2.Gray-Level Co-Occurrence Matrix (GLCM)related to14Measures :

1. **A. Contrast** (this is also called "sum of squares variance" and occasionally “inertia”)

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$$

Contrast equation

Explanation:

When i and j are equal, the cell is on the diagonal and (i-j)=0. These values represent pixels entirely similar to their neighbour, so they are given a weight of 0 (no contrast). If i and j differ by 1, there is a small contrast, and the weight is 1. If i and j differ by 2, contrast is increasing and the weight is 4. The weights continue to increase exponentially as (i-j) increases.

1. B. **Dissimilarity** (Contrast Group)

Instead of weights increasing *exponentially* (0, 1, 4, 9, etc.) as one moves away from the diagonal as Contrast did, the dissimilarity weights increase *linearly* (0,1,2,3 etc.).

$$\sum_{i,j=0}^{N-1} P_{i,j}|i-j|$$

1.C. Homogeneity (**Inverse Difference Moment**) (Contrast group)

Dissimilarity and Contrast result in *larger* numbers for more windows showing more contrast. If weights *decrease* away from the diagonal, the calculated texture measure will be larger for windows with little contrast. Homogeneity weights values by the *inverse* of the Contrast weight, with weights decreasing exponentially away from the diagonal:

$$\sum_{i,j=0}^{N-1} \frac{Pi,j}{1+(i-j)}$$

2. A. Angular Second Moment (ASM), Energy and MAX

ASM and Energy use each P_{ij}as a weight for itself. High values of ASM or Energy occur when the window is very orderly.

$$\sum_{i,j=0}^{N-1} Pi,j$$

ASM equation

The square root of the ASM is sometimes used as a texture measure, and is called **Energy**.

$$\mathbf{Energy} = \sqrt{\mathbf{ASM}}$$

Energy equation

2. B. Entropy

Since ln(0) is undefined, assume that 0 * ln(0) = 0:

$$\sum_{i,j=0}^{N-1} P_{i,j}\left(-\ln P_{i,j}\right)$$

Entropy equation

3. A. GLCM Mean

How GLCM mean differs from the mean of the pixel values in the window:

The GLCM Mean is not simply the average of all the original pixel values in the image window. It is expressed i*n terms of the GLCM*. The pixel value is weighted not by its frequency of occurrence by itself (as in a "regular" or familiar mean equation) but by its frequency of its occurrence *in combination with* a certain neighbour pixel value.

GLCM Mean Equation

$$\mu i = \sum_{i,i=0}^{N-1\infty} i(\mathrm{Pi},\mathrm{i})\ \mu i = \sum_{i,i=0}^{N-1\infty} i(\mathrm{Pi},\mathrm{i})$$

3.B. Variance (Standard Deviation) (Descriptive statistics group)

$$\sigma = \sum_{i,i=B}^{N-1} \mathrm{Pi,i}(\mathrm{i} - \mu\mathrm{i}) \ \sigma = \sum_{i,i=B}^{N-1} \mathrm{Pi,i}(\mathrm{i} - \mu\mathrm{i})$$

Variance equation

$$\sigma\mathrm{i} = \sqrt{\sigma\mathrm{i}\quad^{2}}\sigma\mathrm{i} = \sqrt{\sigma\mathrm{i}\quad^{2}}$$

Standard deviation equation

3. C. Correlation (Descriptive statistics group)

The Correlation texture measures the linear dependency of grey levels on those of neighbouring pixels

$$\sum_{i,i=0}^{N-1} Pi,i\left(\frac{(i-ui)(i-ui)}{\sqrt{(\sigma i)(\sigma i)}}\right)$$

.5-Binarized StatisticalImaga Features(BSIF)

Overview

A local image descriptor is constructed by binarizing the responses to linear filters • In contrast to previous binary descriptors, the filters are learnt from natural images using independent component analysis (ICA) • The proposed descriptor performs well in texture classification and face recognition tasks

5.1.Method

Given an image patch X of size L*L pixels and a linear filter Wi of the same size.

Tha filter reponse Si is obtained by

$$\delta i = \sum_{u,v} Wi(u,v)X(u,v) = wixi$$

where vector notation is introduced in the latter stage . if we have n linear filters Wi, we may stack them to matrix W and compute all responses at once :

s = Wx.

Given random sample of natural image patches ,we determine the filters Wi so that the elements si of s are as independent as possible when consedred as random variables .

The binary code string b.which corresponds to image patch x , is obtained by binarizing each elements Si of as follows ;

$$bi = \begin{cases} 1 \text{ ifsi>0} \\ 0 \text{ otherwise} \end{cases}$$

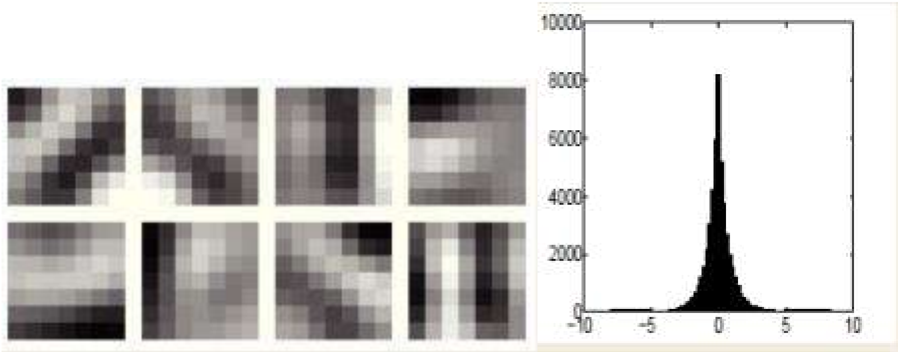


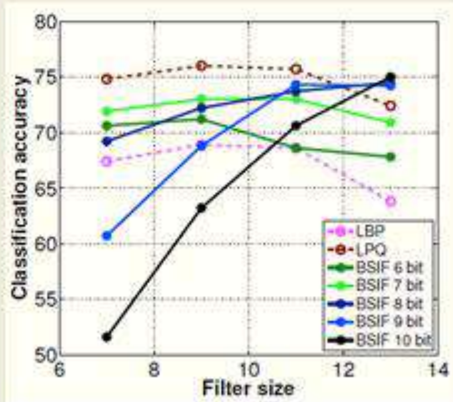
Figure29:Left: Examples of eight learned filters of size 7x7 pixels Right: A typical histogram of filter response values (heavy-tailed)

5.2.Results

•We experimented our approach in two tasks: texture classification (Outex and CUReT databases) and face recognition (FRGC database) • In both cases the classification was performed using nearest neighbor classifier and chi-squared distance metric for descriptor histograms

Face recognition

Figure 4. A sample gallery image and two probe images images from FRGC (top), and corresponding BSIF codes. The blur in the probe images is clearly observable.



(c) FRGC

Conclusion

In this chapter we discussed a set of algorithms that were studied and used in this project and in the next chapter we can complete the rest of them and how we work in this project

Chapter 3

Results and Discussion

Introduction:

Our work consists of designing the identification system by recognizing the ear. There are many necessary steps, the extraction features are the most important steps because the performance of the system depends on the results and durability. In this chapter we will estimate the results obtained based on IITD data under different conditions and methods.

1.Experimental setup

1.1.Database used:

Many databases with information that assess ear recognition systems are available. However, these databases are generally adapted to the needs of certain recognition algorithms; each has been built on various acquisition conditions of ear images, as well as the number of sessions per person.

1.1.1.Delhi I:

This database was obtained at the IITD (Indian Institute of Technology in Delhi), during October 2006 - June 2007. They used a simple image configuration. All images are obtained from a touchless space using a simple image configuration and the image is executed in the internal environment. This data set was obtained from 126 different topics and each topic contains at least three images of the ear. All materials in the database are 14 to 58 years old. A 793 image set is sequentially numbered per user with Integer / Identification. This database provides automatically-sized, 50x180-pixel ear images that are available in the format

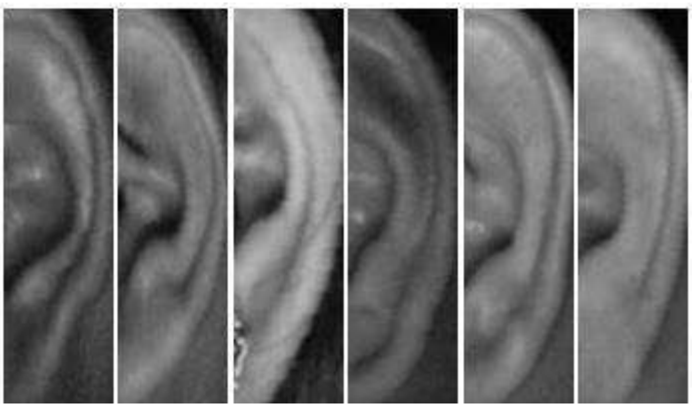


Figure 17:Representative samples from IITD I dataset (126 subjects).

1.1.2. Delhi II:

Compared with the first version, this version does not change a lot, it contained 471 images, it is available and it acquired by 221 different subjects and every subject has three ear images or more. The resolution of the images is 272 x 204 pixels and all these images are in the JPEG format. besides the original images, this database also supplies the images of ear automatically normalized and cut by size 50 x 180pixels.

Each of these images are named as ' XXX_Y.bmp ', where XXX represent the identification number of the subject and Y represent the number of subjectsample.

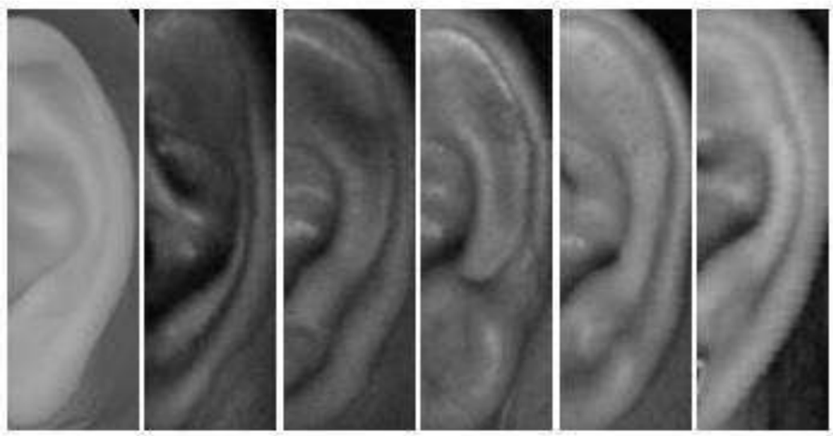


Figure 18:Representative samples from IITD II dataset (221 subjects).

2.Separation of databases:

To develop an application of ear recognition, it is necessary to have two databases: a base to make the training and another one to test techniques and determine their performances, but there is no rule to determine this division in a quantitative way. It often results from a compromise taking into account the number of data which we have and of time to make thetraining.

In the series of test that we made the base was split in the following way

· **Test images**: the first image of every individual we served for the realization of thetests.

· **Training images**: the images which stay of every individual served for the phase of training.

The purpose is to estimate the rate of recognition of various algorithms presented, by following a protocol of test based on the measure of recognition rate.

2.1.Performances of a system of ear recognition:

The performances of a recognition system depend on many factors which intervene at several levels and which can limit the degree of precision. However, it would be sensible to be interested in these factors before measuring the performance of a recognition system. We quote here the main factors[15].

- The environment at the time of theacquisition.
- The various positions of thesensors.
- The quality of thesensors.
- The bad interaction between the user and thesensors.

To estimate the performances of an identification system, we calculate the accuracy. The error committed by this type of system is to attribute to the presented individual an identity other than his. The performances of these systems are measured by the accuracy[15].

$$\textbf{Accuracy} = \frac{\text{Number of tests corresponding to a correct identification}}{\text{Total number of tests}}$$

2.2.The language used (MATLAB R2013a, version9.0.0.341360):

MATLAB is a programming language consists of a development environment, a set of complementary modules and the libraries which spread the features of MATLAB for the development of its important property and its calculation simplicity, what allows analyzing images as challenge: the real time regulations.

The name of MATLAB is synonymic of *MATRIX LABORATORY*. MATLAB is a high performance language of technical calculation. It integrates the calculation, the visualization and the programming in an environment easy to use, where the problems and the solutions are expressed in a familiar mathematical notation[16].

The classic use integrates.

- The development ofalgorithms.
- The mathematics and thecalculation.
- The modeling, the simulation and theprototyping.
- The analysis of data, the exploration and thevisualization.
- The development of applications including the strengthening of the user graphical interface.

Figure 19:The MATLAB logo.

3.Experimentalresults:

3.1.The system of ear Recognition: principles andexperimentations:

The problem of the ear recognition is defined as follows: being given an image of ear the corresponding subject of which we wish to determine. To do it, it is necessary to have reference images, in the form of an ear database of all the persons known by the system. In every image is associate a vector of features, these features are supposed to be invariant for the same person, and different from a person to other one. The recognition consists in comparing the vector of ear features to recognize with each ears of the database. This allows to find the subject or the person having the ear the most resembling, which is the one whose vector is the most similar

.

3.2.First experiment (thepre-processing):

The primary processing step is achieved initially to improve the quality of the ear images. We used the noise smoothing and block division (16 x 16 pixels) to set the image for the next step..

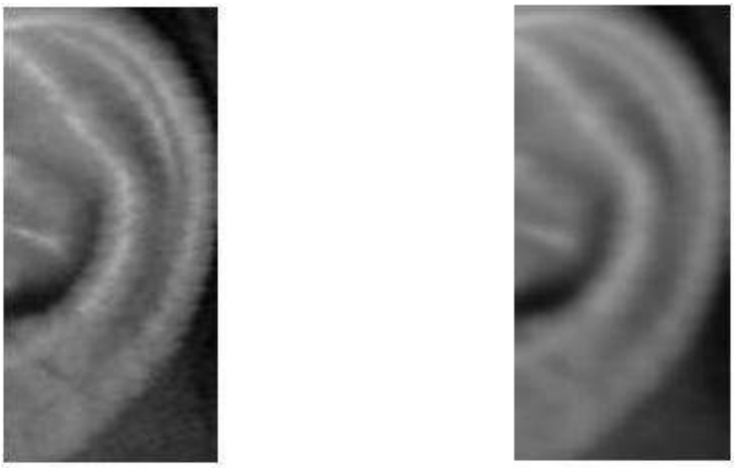


Figure 20:(a) ear image before Gaussian smoothing, (b) ear image after Gaussian smoothing.

3.3.Second experiment:

3.3.1.**By the LBP method :**

In our work we extracted the features by various methods for all the images in two cases, the first case where the extraction is made for the full image, and the second case where the image is divided into blocks of 16*16 pixels.

The (Figure 36) below show the variation of the clean values of the array and the properties extracted by standard and irregular LBP for the image of the IIT Delhi database. Note on the curve that there is a significant difference between the values of extracting a divided image and an indivisible image. We can also observe the difference between both types of LBP method.

3.3.2.By the GLCM method:

Also, for the GLCM method, there is a significant difference between the extraction of features for a complete image and a divided image, where we note that vector image extraction is only 4 values, and the vector image is divided into value

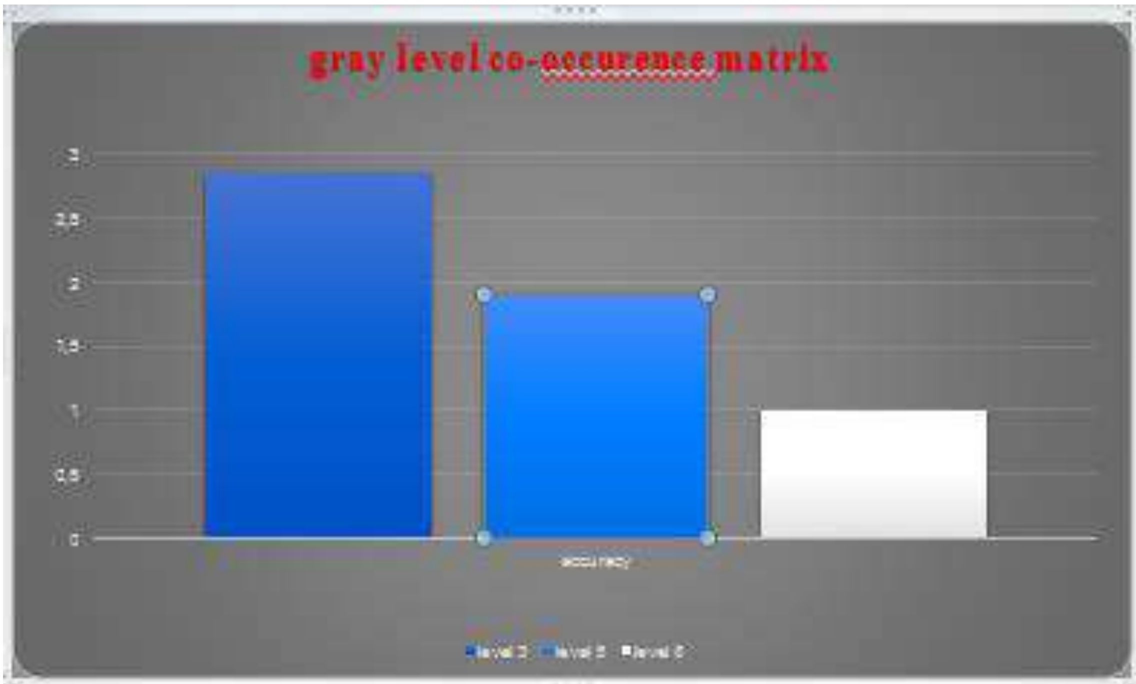


Figure 21:By the GLCM Method

3.4.Third experiment (theclassification):

In this section, we apply three methods of classification to our database. The training of every classifier is optimized with its own techniques to fix their parameters

3.4.1- The classification methods based on LBP (uniform and not uniform):

In this step we compare the performance of the two works(Figure 39,Figure 40), showing the effect of the division of images, where the performance of all works in this case increases.

3.4.2- The classification methods based on GLCM:

The big difference was illustrated in this experiment, a very significant improvement of which the values of the three classifiers performances knew in the case of division of the images, where the accuracy of classifier KNN affect 81.5 % which is of course the biggest proportion followed by the SVM which was classified the third before the division of the images

number of person	GLCM	Level
5	28%	3
5	71,40%	4
60	2,85%	3
60	1,90%	5
60	1%	8

Figure 22:The classification methods based on GLCM.

The following table makes the comparison of the various percentages of the classifiers accuracy for the three methods uniform LBP, no uniform LBP and GLCM, in the case of the full images and the divided images, where we observe that the classification using the method GLCM with division is the most successful followed by uniform LBP with division.

Presentation of theapplication:

In this section we present the different aspects of our gratitude system.

We start with the project presentation interface, a user-friendly, simple interface that explains the key processes of the ear recognition system:

Browser image: to select the test image from the gallery.

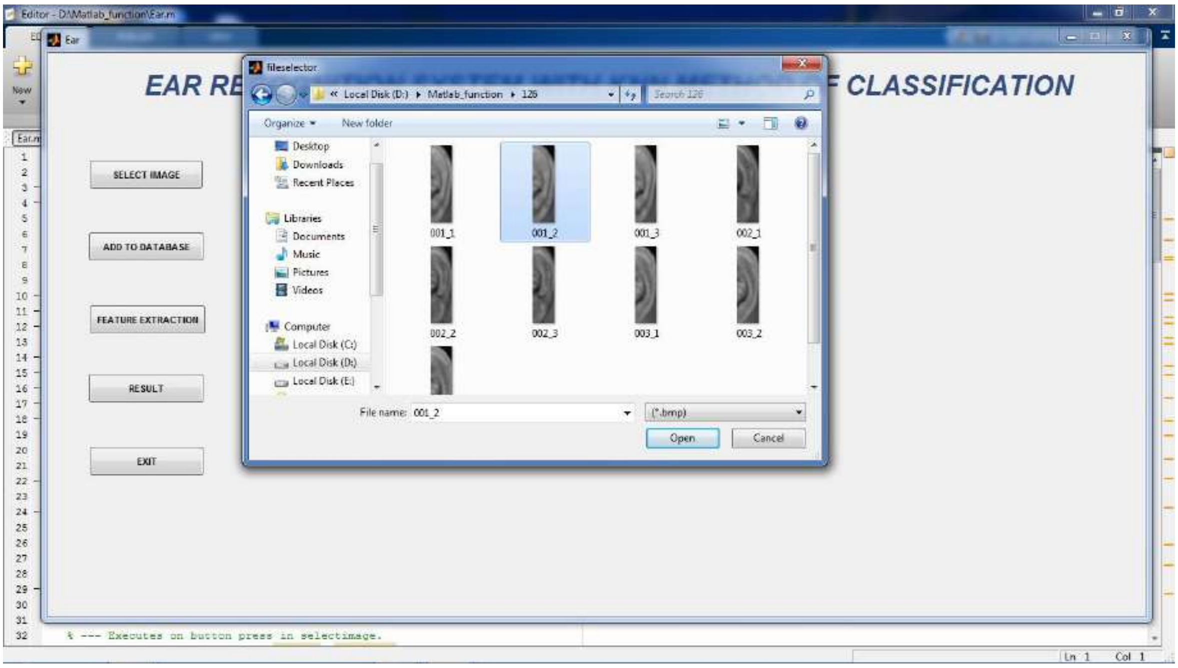


Figure 23:Select the test image from the gallery.

In order to choose features to be worked out

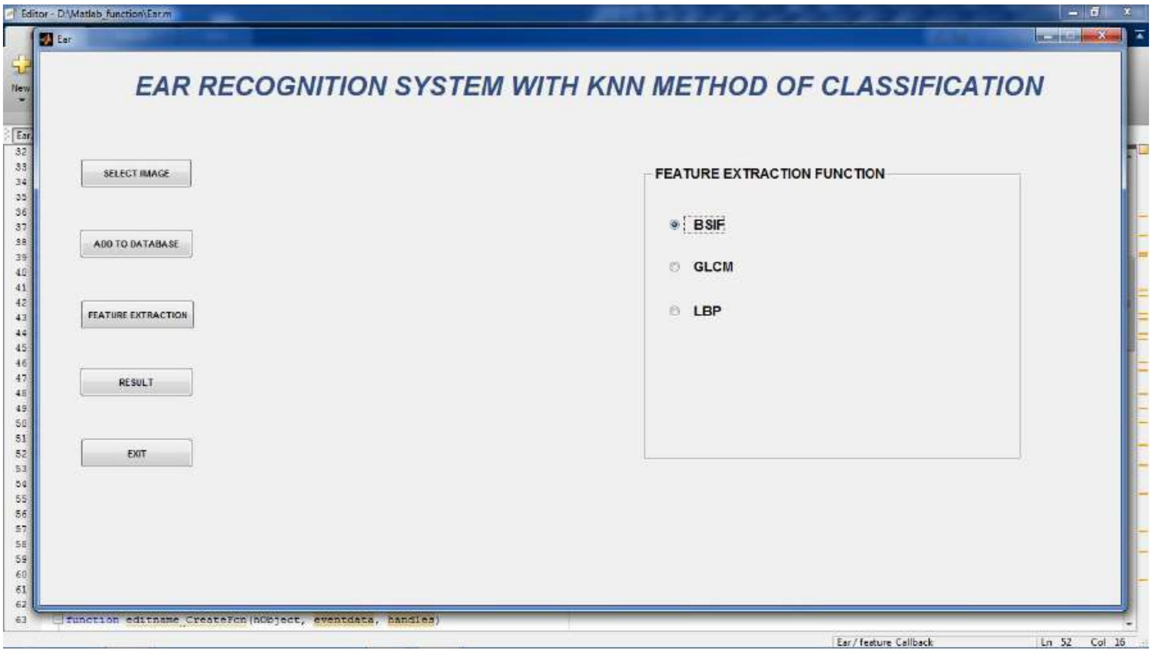


Figure 24:Interface of the combination methods.

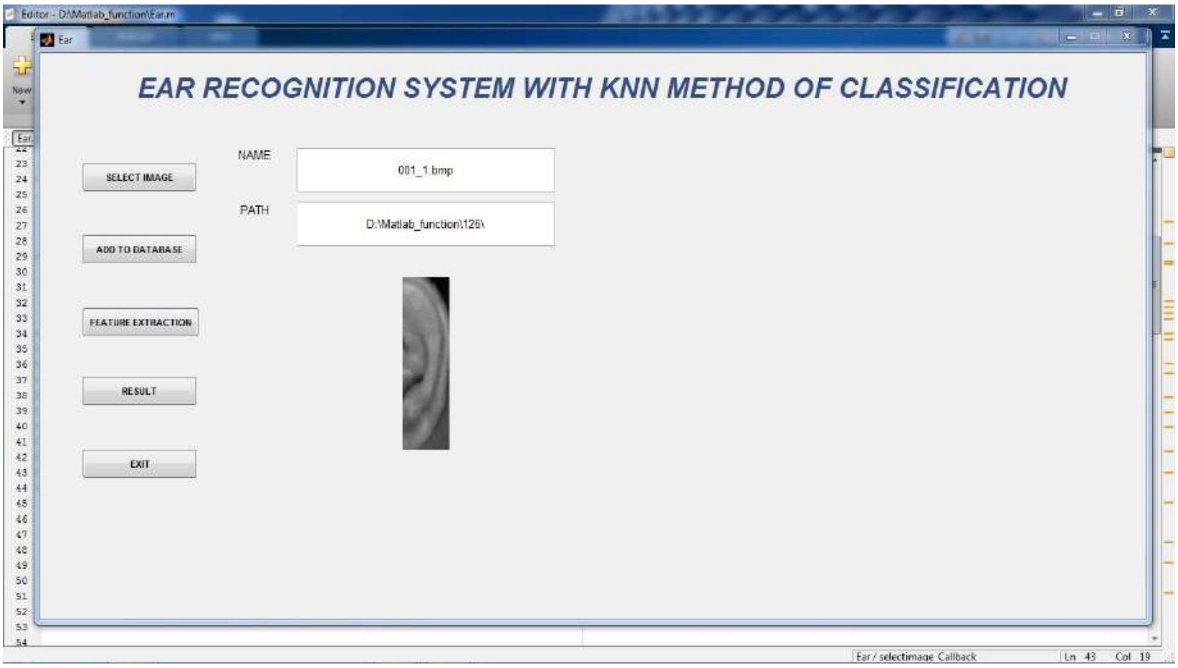


Figure 25:Interface represents the step of features extraction.

Conclusion:

In this chapter, we introduced an ear recognition application based on GLCM and LBP algorithms, BSIF, and we also presented the various results obtained for each algorithm also by workbooks and methods of collection. Our ear recognition system is applied to the IIT Delhi Ear Database. We can observe that the BSIF method is the most effective way to .extract features. We also found that many external factors affect the quality of the estimate

GENERAL CONCLUSION

Biometrics is a field at the same time fascinating and complex. Through very sophisticated mathematical tools, tries to distinguish between individuals and obliges us to work in a very large diversity context. This diversity also finds itself in the large number of algorithms proposed in ear recognition. In this report, we were interested in the problem of .ear recognition

Our work is to develop a powerful algorithm aimed at identifying the individual through his or her ear using two of the most widely used methods in this field. The first technique .is LBP and the second is GLCM and the third is BSIF

During this work, we emphasized the fatal impact on the accuracy of the system, so we suggested some solutions that were evaluated during the work. The BSIF method remains an effective and simple method in the classification step, followed by GLCM, but after the group is applied, LBP is categorized as the first method. For all these reasons we have chosen this approach to recognize the ear. We appreciate that we have realized a system that responds to the goal we initially established, which is worth knowing about .implementing a system that allows individuals to be identified and control access

Through perspectives, the other is to apply this system to the rules of other ears that offer strong differences in lighting. Next, one of the major challenges is to be better able to master the forms of the environment, which still disturb identity recognition systems, the latest developments in 3D image capture technology allowed to create fairly robust .systems of recognition compared to 2D

If biometrics represent a significant share of the economic level, research, particularly in .the area of ear recognition, offers another area of open investigation

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Abstract

In the last decade, ear recognition has been the subject matter of several researches in the field of computer vision due to its interesting applications, especially the forensic applications. In this work, we develop a new system for human ear print recognition based on local texture descriptors. In particular, we employ three well-known descriptors namely Local Binary Patterns, Grey-Level Co-Occurrence matrix (GLCM) and BinariazeStatistical Image Features (BSIF), where K-Nearest Neighbour classifier is used to perform classification. We carried out experiments on the IIT-Delhi-I dataset which is made up of 493 images from 125 subjects, where an overall accuracy of % is reached.

ملخص

في العقد الماضي ، كان التعرف على الأذن موضوع العديد من الأبحاث في مجال رؤية الكمبيوتر بسبب تطبيقاته المثيرة للاهتمام ، وخاصة تطبيقات الطب الشرعي. في هذا العمل ، نطور نظامًا جديدًا للتعرف على بصمات الأذن البشرية استنادًا إلى واصفات النسيج المحلية. على وجه الخصوص ، نحن نوظف ثلاثة واصفات معروفة وهي: الأنماط الثنائية المحلية ، مصفوفة التواجد المشترك على مستوى الرمادي (GLCM) وميزات صورة إحصائية (BSIF)BinariazeStatistical Image Features ، حيث يتم استخدام مصنف K-Nearest Neighbor لإجراء التصنيف. لقد أجرينا تجارب على مجموعة بيانات IIT-Delhi-I المؤلفة من 493 صورة من 125 موضوعًا ، حيث تم الوصول إلى دقة إجمالية قدرها٪.