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Feature Recognition from Histogram and Eigen Algorithm in Digital Image Processing

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***Abstract*— Iris is an internal organ of the eye, which is well protected from the environment and its patterns are apparently stable throughout the life. So that can be used for recognition or security purpose as in it chances of failure of recognition or identification of user is less. So in this field many approaches have been developed for identification of iris or can say that iris recognition but those algorithms have many or some disadvantages. However researchers are in search of such algorithm which will be more efficient and reliable which can enhance the iris recognition criteria in field of security or identity verification.**

In this research work a proposed methodology is developed in which main focus is on iris identification enhancement this methodology includes the concept of feature extraction based iris recognition. But the technique which is proposed in this work is bit different from the traditional ones. Proposed work includes the Eigen feature extraction algorithm which gives quit efficient as compared with earlier solely working algorithms.

***Keywords*— Histogram, Iris and Eigen Algorithm**.

I. Introduction

Iris recognition is an automated method of biometric identification that uses mathematical pattern-recognition techniques on video images of the irides of an individual's eyes, whose complex random patterns are unique and can be seen from some distance. Not to be confused with other, less prevalent, ocular-based technologies, retina scanning and eye printing, iris recognition uses camera technology with subtle infrared illumination to acquire images of the detail-rich, intricate structures of the iris externally visible at the front of the eye. Digital templates encoded from these patterns by mathematical and statistical algorithms allow the identification of an individual or someone pretending to be that individual. Databases of enrolled templates are searched by matcher engines at speeds measured in the millions of templates per second per (single-core) CPU, and with remarkably low false match rates. Many millions of persons in several countries around the world have been enrolled in iris recognition systems, for convenience purposes such as passport-free automated border-crossings, and some national ID systems based on this technology are being deployed. A key advantage of iris recognition, besides its speed of matching and its extreme resistance to false matches, is the stability of the iris as an internal, protected, yet externally visible organ of the eye. When locating the iris there are two potential options. The software could require the user to select points on the image, which is both reliable and fairly accurate, however it is also time consuming and implausible for any real-world application. The other option is for the software to auto-detect the iris within the image. This process is computationally complex and introduces a source of error due to the inherent complexities of computer vision. However, as the software will then require less user interaction it is a major step towards producing a system which is suitable for real-world deployment, and thus became a priority for extending the program specification.

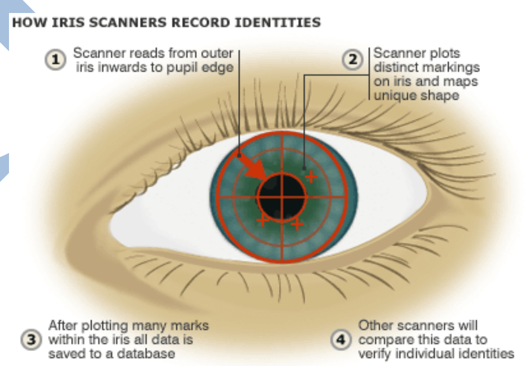


FIG.1. How Iris Scanners Record Identities

Locating the iris is not a trivial task since its intensity is close to that of the sclera1 and is often obscured by eyelashes and eyelids. However the pupil, due to its regular size and uniform dark shade, is relatively easy to locate. The pupil and iris can be approximated as concentric and this provides a reliable entry point for auto detection. Soft computing techniques of neural network Following two approaches of the neural network are used for enhancing the security in iris recognition system: Learning Vector Quantization (LVQ) Learning Vector Quantization is a prototype-based supervised classification algorithm. LVQ can be understood as a special case of an artificial neural network. LVQ is one of the competitive neural networks. LVQ is a pattern classification method; each output node is represented as a class. The weight vector of an output node is called a reference or codebook vector (CV). The LVQ attempts to adjust the weights to approximate a theoretical bayes classifier. The result obtained depends on the majority

voting among several weak classifiers Input vectors are classified by assigning them as a class label of the weight vector closest to the input vector. The result obtained depends on the majority voting among several weak classifiers.
The LVQ consisting of two layers; the first layer is the input layer which contains the input neurons, while the second layer is the output layer that contains output neurons. The final step is the pattern matching of the Iris image with the stored templates from the database. The Following figure shows Pattern matching process. These patterns are used to create templates for Iris recognition. It will work fine for less number of users, but it is not recommended for large number of users since it requires large storage memory. Iris recognition is the best of breed authentication process available today. While many mistake it for retinal scanning, iris recognition simply involves taking a picture of the iris; this picture is used solely for authentication. But what makes iris recognition the authentication system of choice?

- Stable - the unique pattern in the human iris is formed by 10 months of age, and remains unchanged throughout one's lifetime
- Unique - the probability of two rises producing the same code is nearly impossible
- Flexible - iris recognition technology easily integrates into existing security systems or operates as a standalone
- Reliable - a distinctive iris pattern is not susceptible to theft, loss or compromise

Non-Invasive - unlike retinal screening, iris recognition is non-contact and quick, offering unmatched accuracy when compared to any other security alternative, from distances as far as 3" to 10"
In this paper the histogram recognition and Eigen algorithm comparison study for feature recognition in digital image processing is investigated. The basics of iris recognition problems, advantages & its operating procures along with colour histogram, neural network and support vector machine (SVM) are presented in Section II. The methodology of the investigations, problem formulation , Eigen feature extraction and conclusions are presented in Section III.

II. IRIS RECOGNITION PROBLEMS, ADVANTAGES & ITS OPERATING PROCURE

An iris recognition problem is subdivided into three sub-problems
A) Iris Segmentation:
This is the process in which iris part is separated from rest of the eye images. Daughman’s method is still the most accepted and adopted technique for iris segmentation. In this work we have proposed a unique color based iris segmentation technique which does not require any user input for segmentation.
B) Iris Feature Extraction:
The features of Iris images are mainly categorized as
i) Gray Level Co-occurrence features or texture features.
ii) Phase based features
iii) Features on the wavelet and Fourier domain
iv) Statistical features
v) Shape based features.

C) Classification:
There are various classifiers presented for iris recognition. But most of the biometric recognition systems are migrated to kernel based techniques which reduces the dimensionality of the extracted feature vectors by converting scalar features to vector feature space. Therefore vector oriented classifiers have got more significance over other classifiers like neural network and nearest neighbor classifier. Support vector machine is essentially a two class classification problem. This technique transforms feature vector from low dimensionality plane to high dimensionality plane in such a way that features are easily separable. Various kernel functions like Gaussian, RBF and Linear functions are used for the same transformation. In this work we develop a 64 class iris recognition solution for color iris database.

ADVANTAGE OF IRIS RECOGNITION

Iris recognition is an attractive technology for identity authentication for several reasons.

1. The smallest outlier population of all biometrics. Few people can't use the technology, as most individuals have at least one eye. In a few instances even blind persons have used iris recognition successfully, as the technology is iris pattern-dependent, not sight dependent.
2. Iris pattern and structure exhibit long-term stability. Structural formation in the human iris is fixed from about one year in age and remains constant (barring trauma, certain rare diseases, or possible change from special some ophthalmologic surgical procedures) over time. So, once a individual is enrolled, re-enrolment requirements are infrequent. With other biometric technologies, changes in voice timbre, weight, hairstyle, finger or hand size, cuts or even the effect of manual labor can trigger the need for re-enrolment.
3. Ideal for Handling Large Databases. Iris recognition is the only biometric authentication technology designed to work in the 1-n or exhaustive search mode. This makes it ideal for handling applications requiring management of large user groups, such as a National Documentation application might require.. Large databases are accommodated without degradation in authentication accuracy. Iris Access platforms integrate well with large database back ends like Microsoft SQL and Oracle 9i.
4. Unmatched Search Speed in the one to many search mode is unmatched by any other technology, and is limited not by database size, but by hardware selected for server management. In a UK Government-commissioned study, Iris ID's IrisAccess platform searched records nearly 20 times faster than the next fastest technology. Iris ID has developed a high speed matching engine, IrisAccelerator™, designed to deliver 10 million+ matches per second.
5. Versatile for the One to Many, One to One, Wiegand and Token Environments. While initially designed to work in one-to-many search mode, iris recognition works well in 1-1 matching, or verification mode, making the technology ideal for use in multifactor authentication environments where PINs, or tokens like prox or smartcards are used. In a token environment,

many privacy issues related to biometric database management are moot, as the user retains control of biometric data – a small template of 512 bytes per iris.

6. Safety and Security Measures in Place. Iris recognition involves nothing more than taking a digital picture of the iris pattern (from video), and recreating an encrypted digital template of that pattern. 512-byte iris templates are encrypted and cannot be re-engineered or reconstituted to produce any sort of visual image. Iris recognition therefore affords high level defense against identity theft, a rapidly growing crime. The imaging process involves no lasers or bright lights and authentication is essentially non-contact.
7. Convenient, Intuitive User Interface. Using the technology is an almost intuitive experience, requiring relatively little cooperation from subjects. Proximity sensors activate the equipment, which incorporates mirror-assisted alignment functionality. Audio auto-positioning prompts, automated image capture, and visual and audio authentication decision-cueing completes the process.

OPERATING PRINCIPLE

An iris-recognition algorithm can identify up to 200 identification points including rings, furrows and freckles within the iris. First the system has to localize the inner and outer boundaries of the iris (pupil and limbus) in an image of an eye. Further subroutines detect and exclude eyelids, eyelashes, and specular reflections that often occlude parts of the iris. The set of pixels containing only the iris, normalized by a rubber-sheet model to compensate for pupil dilation or constriction, is then analyzed to extract a bit pattern encoding the information needed to compare two iris images. Human iris identification process is basically divided into four steps,

1. Localization - The inner and the outer boundaries of the iris are calculated. Localization of function, locating psychological functions in the brain or nervous system; see Linguistic intelligence. Localization of sensation, ability to tell what part of the body is affected by touch or other sensation; see Allochiria. Nuclear localization signal, an amino acid sequence on the surface of a protein which acts like a 'tag' to localize the protein in the cell. Sub-cellular localization, the organization of cellular components into different regions of the cell
2. Normalization - Iris of different people may be captured in different size, for the same person also size may vary because of the variation in illumination and other factors. Database normalization is the process of organizing the fields and tables of a relational database to minimize redundancy. Normalization usually involves dividing large tables into smaller (and less redundant) tables and defining relationships between them. The objective is to isolate data so that additions, deletions, and modifications of a field can be made in just one table and then propagated through the rest of the database using the defined relationships.
3. Feature extraction - Iris provides abundant texture information. a feature vector is formed which consists of the ordered sequence of features extracted from the various representation of the iris images. In pattern recognition and in image processing, feature extraction is a special form of dimensional reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.
4. Matching - The feature vectors are classified through different thresholding techniques like Hamming Distance, weight vector and winner selection, dissimilarity function, etc.
5. In the case of Daugman's algorithms, a Gabor wavelet transform is used. The result is a set of complex numbers that carry local amplitude and phase information about the iris pattern. In Daugman's algorithms, most amplitude information is discarded, and the 2048 bits representing an iris pattern consist of phase information (complex sign bits of the Gabor wavelet projections). Discarding the amplitude information ensures that the template remains largely unaffected by changes in illumination or camera gain (contrast), and contributes to the long-term usability of the biometric template.
6. For identification (one-to-many template matching) or verification (one-to-one template matching, a template created by imaging an iris is compared to stored template(s) in a database. If the Hamming distance is below the decision threshold, a positive identification has effectively been made because of the statistical extreme improbability that two different persons could agree by chance ("collide") in so many bits, given the high entropy of iris templates.

COLOR HISTROGRAM

In image processing and photography, a color histogram is a representation of the distribution of colors in an image. For digital images, a color histogram represents the number of pixels that have colors in each of a fixed list of color ranges, that span the image's color space, the set of all possible colors.

The color histogram can be built for any kind of color space, although the term is more often used for three-dimensional spaces like RGB or HSV. For monochromatic images, the term intensity histogram may be used instead. For multi-spectral images, where each pixel is represented by an arbitrary number of measurements (for example, beyond the three measurements in RGB), the color histogram is N-dimensional, with N being the number of measurements taken. Each measurement has its own wavelength range of the light spectrum, some of which may be outside the visible spectrum.

If the set of possible color values is sufficiently small, each of those colors may be placed on a range by itself; then the histogram is merely the count of pixels that have each possible color. Most often, the space is divided into an appropriate number of ranges, often arranged as a regular grid, each containing many similar color values. The color histogram may also be represented and displayed as a smooth function defined over the color space that approximates the pixel counts.

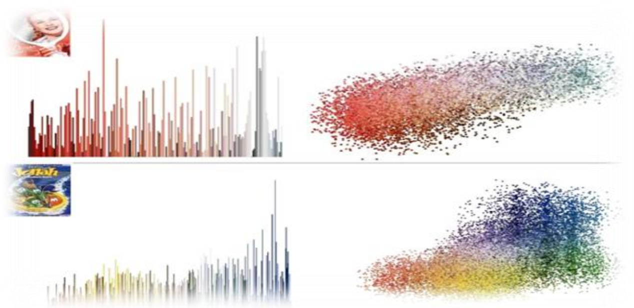


FIG. 2. A Color Histogram represents the distribution of colors in an image.

Like other kinds of histograms, the color histogram is a statistic that can be viewed as an approximation of an underlying continuous distribution of colors values. An image histogram refers to the probability mass function of the image intensities. This is extended for color images to capture the joint probabilities of the intensities of the three color channels. More formally, the color histogram is defined by, $h_{A,B,C}(a,b,c) = N \cdot \mathrm{Pr}ob(A=a, B=b, C=c)$ where A , B and C represent the three color channels (R,G,B or H,S,V) and N is the number of pixels in the image. Computationally, the color histogram is formed by discrediting the colors within an image and counting the number of pixels of each color. Since the typical computer represents color images with up to 224 colors, this process generally requires substantial quantization of the color space. The main issues regarding the use of color histograms for indexing involve the choice of color space and quantization of the color space. When a perceptually uniform color space is chosen uniform quantization may be appropriate. If a non-uniform color space is chosen, then non-uniform quantization may be needed. Often practical considerations, such as to be compatible with the workstation display, encourage the selections of uniform quantization and RGB color space. The color histogram can be thought of as a set of vectors. For gray-scale images these are two dimensional vectors. One dimension gives the value of the gray-level and the other the count of pixels at the gray-level. For color images the color histograms are composed of 4-D vectors. This makes color histograms very difficult to visualize. There are several lossy approaches for viewing color histograms; one of the easiest is to view separately the histograms of the color channels. This type of visualization does illustrate some of the salient features of the color histogram neural network

The simplest definition of a neural network, more properly referred to as an 'artificial' neural network (ANN), is provided by the inventor of one of the first neuro-computers, Dr. Robert Hecht-Nielsen. He defines a neural network as: "...a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.

The modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes. Thus the term has two distinct usages:

i) ―Biological neural networks‖ are made up of real biological neurons that are connected or functionally related in the peripheral nervous system or the central nervous system. In the field of neuroscience, they are often identified as groups of neurons that perform a specific physiological function in laboratory analysis. Understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system. The real, biological nervous system is highly complex: artificial neural network algorithms attempt to abstract this complexity and focus on what may hypothetically matter most from an information processing point of view. Good performance or performance mimicking animal or human error patterns, can then be used as one source of evidence towards supporting the hypothesis that the abstraction really captured something important from the point of view of information processing in the brain. Another incentive for these abstractions is to reduce the amount of computation required to simulate artificial neural networks, so as to allow one to experiment with larger networks and train them on larger data sets. An artificial neural network usually called neural network, is a mathematical model or computational model that is inspired by the structure and functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it 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. Modern neural networks are non-linear statistical data modelling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data.

ii) ―Artificial neural networks‖ are composed of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons). Artificial neural networks may either be used to gain an In "Neural Network Primer: Part I" by Maureen Caudill, AI Expert, Feb. 1989

ANNs are processing devices (algorithms or actual hardware) that are loosely modeled after the neuronal structure of the mammalian cerebral cortex but on much smaller scales. A large ANN might have hundreds or thousands of processor units, whereas a mammalian brain has billions of neurons with a corresponding increase in magnitude of their overall interaction and emergent behavior. Although ANN researchers are generally not concerned with whether their networks accurately resemble biological systems, some have. For example, researchers have accurately simulated the function of the retina and modeled the eye rather well.

Although the mathematics involved with neural networking is not a trivial matter, a user can rather easily gain at least an operational understanding of their structure and function.

BASICS OF NEURAL NETWORKS

Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer output as shown in the graphic below.

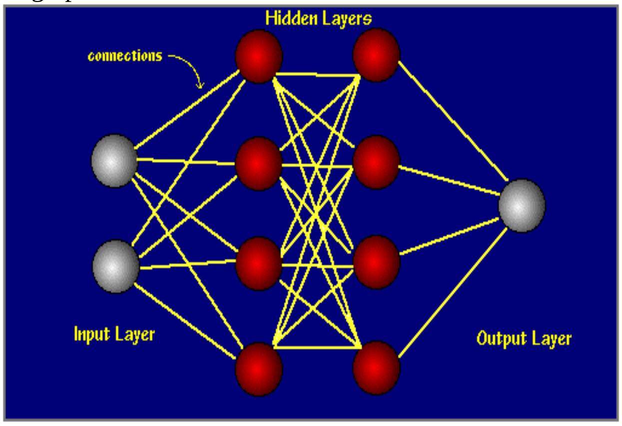


FIG. 3 Neural networks are typically organized in layers.

ANNs contain some form of 'learning rule' which modifies the weights of the connections according to the input patterns that it is presented with. In a sense, ANNs learn by example as do their biological counterparts; a child learns to recognize dogs from examples of dogs.

Although there are many different kinds of learning rules used by neural networks, this demonstration is concerned only with one; the delta rule. The delta rule is often utilized by the most common class of ANNs called 'back propagation neural networks' (BPNNs). Back propagation is an abbreviation for the backwards propagation of error.

With the delta rule, as with other types of back propagation, 'learning' is a supervised process that occurs with each cycle or 'epoch' (i.e. each time the network is presented with a new input pattern) through a forward activation flow of outputs, and the backwards error propagation of weight adjustments. More simply, when a neural network is initially presented with a pattern it makes a random 'guess' as to what it might be. It then sees how far its answer was from the actual one and makes an appropriate adjustment to its connection weights. More graphically, the process looks something like this as per figure no 4:

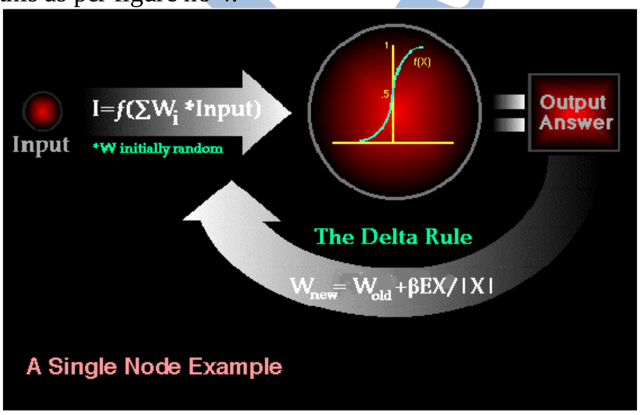


FIG. 4. A Single Node Example

Note also, that within each hidden layer node is a sigmoid activation function which polarizes network activity and helps it to stabilize.

SUPPORT VECTOR MACHINE (SVM)

In machine learning, support vector machines (SVMs, also support vector networks are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

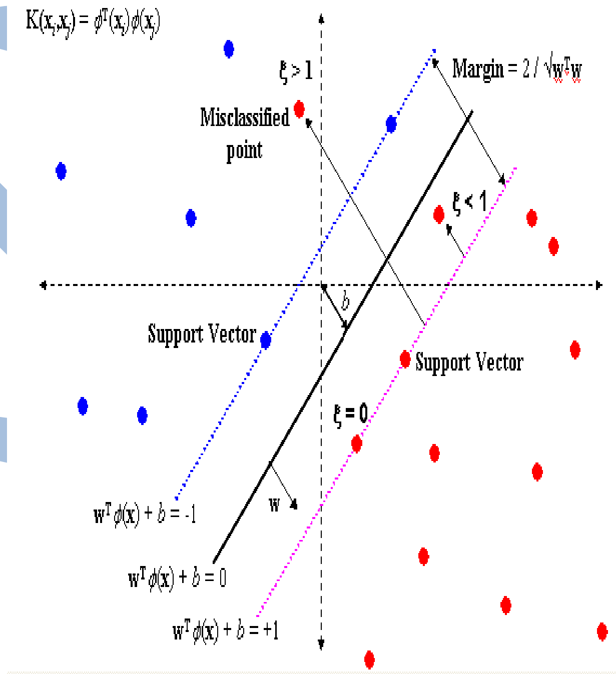


FIG. 5. Support Vector Networks

More formally, a support vector machine constructs a hyper plane or set of hyper planes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. Whereas the original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by SVM schemes are designed to ensure that dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function $K(x, y)$ selected to suit the problem. The hyper planes in the higher-dimensional space are defined as the set of points whose dot product with a vector in that space is constant. The vectors defining the hyper planes can be chosen to be linear combinations with parameters α_i of images of feature vectors that occur in the data base. With this choice of a hyper plane, the points in the feature space that are mapped into the hyper plane are defined by the relation: $\sum_i \alpha_i K(x_i, x) = \mathrm{constant}.$ Note that if $K(x, y)$becomes small as y grows further away from x, each term in the sum measures the degree of closeness of the test point x to the corresponding data base point . In this way, the sum of kernels above can be used to measure the relative nearness of each test point x to the data points originating in one or the other of the sets to be discriminated. Note the fact that the set of points x mapped into any hyper plane can be quite convoluted as a result, allowing much more complex discrimination between sets which are not convex at all in the original space.

III. METHODOLOGY

- Firstly an dataset of static iris images will be used for the recognition purpose
- Next step is to format the dataset images for the feature extraction
- Eigen feature extraction algorithm is used for extracting the matching features for classification
- The features are further pass to creating a network for training so that when testing is done we have to extract the features of dataset which will reduce the time consumption
- Next step is to select the testing image of can say to give the iris image for matching
- User will select the image which is to be tested
- Same feature extraction of Eigen is applied on testing image so as to convert the image in same format as its database is.
- These feature are pass to database created of images in dataset and evaluate the matching criteria
- Finally system will decide that whether image is matched or not
- Same will be executed many times so as to calculate the accuracy of system

IV. PROBLEM FORMULATION

Iris recognition is distinguee as two internal and apparent recognition. Whereas performing arts internal recognition there occur scores of problems relating to matching of the patterns and points taken for identification. Many algorithms have been developed, but there still comes difficulties in iris recognition of eye. Iris methods are more reliable than face and finger recognition. But in image capturing, localizing the iris position and optimizing it, there occurs a lot all obstacles.

Many approaches have been developed as histogram matching, color based matching and many more but in these algorithm if a bit change occur in the captured image or in image which is to tested the results are not satisfactory. Either the systems using these algorithm are not that much capable to recognize the iris images. So there is a need for such algorithm which can recognize the iris images more efficiently and if bit change in image occurs that can be recognized.

OBJECTIVES

1. Development of Eigen feature extraction based iris recognition system
2. Check the recognition rate of proposed system
3. Analysis of obtained results of proposed system

PROPOSED WORK

In the modern world, a reliable personal identification infrastructure is required to control the access in order to secure areas or materials. Conventional methods of recognizing the identity of a person by using passwords or cards are not altogether reliable, because they can be forgotten, stolen, disc losable, or transferable (Zhang, 2000). Biometric technology, which is based on physical and behavioral features of human body such as face, fingerprint, hand shapes, iris, palm print, keystroke, signature and voice, (Lim et al., 2001, Zhang, 2000, Zhu et al., 1999) has now been considered as an alternative to existing systems in a great deal of application domains such as bank Automatic Teller Machines (ATM), telecommunication, internet security and airport security. Each biometric technology has its own advantages and disadvantages based on their usability and security.

Among the various traits, iris recognition has attracted a lot of attention of security developers. Iris is an internal organ of the eye, which is well protected from the environment and its patterns are apparently stable throughout the life. So that can be used for recognition or security purpose as in it chances of failure of recognition or identification of user is less. So in this field many approaches have been developed for identification of iris or can say that iris recognition but those algorithms have many or some disadvantages. However researchers are in search of such algorithm which will be more efficient and reliable which can enhance the iris recognition criteria in field of security or identity verification.

In this research work a proposed methodology is developed in which main focus is on iris identification enhancement this methodology includes the concept of feature extraction based iris recognition. But the technique which is proposed in this work is bit different from the traditional ones. The approach which is proposed in this thesis work is Eigen feature extraction with addition of neural network for iris recognition. The main advantages of this algorithm are

1. More efficient and easy to understand
2. Fast recognition and matching ability
3. Input data changes acceptability
4. Intelligence system integrity

EIGEN FEATURE EXTRACTION:

EIGEN VALUES AND EIGENVECTORS: An **Eigenvector** of a square matrix $A$is a non-zero vector $v$that, when the matrix multiplies v, yields a constant multiple of v, the latter multiplier being commonly denoted by λ. That is: $Av = \lambda v$(Because this equation uses post-multiplication by, it describes a right Eigenvector). The number $\lambda$is called the **Eigen value** of Acorresponding to

v. If 2D space is visualized as a piece of cloth being stretched by the matrix, the Eigenvectors would make up the line along the *direction* the cloth is stretched in and the line of cloth at the center of the stretching, whose direction isn't changed by the stretching either. The Eigen values for the first line would give the *scale* to which the cloth is stretched, and for the second line the scale to which it's tightened. A reflection may be viewed as stretching a line to scale -1 while shrinking the axis of reflection to scale 1. For 3D rotations, the Eigenvectors form the axis of rotation, and since the scale of the axis is unchanged by the rotation, their Eigen values are all 1. In analytic geometry, for example, a three-coordinate vector may be seen as an arrow in three-dimensional space starting at the origin. In that case, an Eigenvector $v$is an arrow whose direction is either preserved or exactly reversed after multiplication by A. The corresponding Eigen value determines how the length of the arrow is changed by the operation, and whether its direction is reversed or not, determined by whether the Eigen value is negative or positive.

In abstract linear algebra, these concepts are naturally extended to more general situations, where the set of real scalar factors is replaced by any field of scalars (such as algebraic or complex numbers); the set of Cartesian vectors $\mathbb{R}^n$ is replaced by any vector space (such as the continuous functions, the polynomials or the trigonometric series), and matrix multiplication is replaced by any linear operator that maps vectors to vectors (such as the derivative from calculus). In such cases, the "vector" in "Eigenvector" may be replaced by a more specific term, such as Eigen function, Eigen mode, "Eigen face", or "Eigen state". Thus, for example, the exponential function $f(x) = e^{\lambda x}$ is an Eigen function of the derivative operator, $\prime$, with Eigen value λ, since its derivative is $f'(x) = \lambda e^{\lambda x} = \lambda f(x)$.

The set of all Eigenvectors of a matrix (or linear operator), each paired with its corresponding Eigen value, is called the **Eigen system** of that matrix.[2] Any multiple of an Eigenvector is also an Eigenvector, with the same Eigen value. An **Eigen space** of a matrix $A$is the set of all Eigenvectors with the same Eigen value, together with the zero vectors. An **Eigen basis** for $A$is any basis for the set of all vectors that consists of linearly independent Eigenvectors of A. Not every matrix has an Eigen basis, but every symmetric matrix does. The terms **characteristic vector**, **characteristic value**, and **characteristic space** are also used for these concepts. The prefix **Eigen-** is adopted from the German word *Eigen* for "own-" or "unique to", "peculiar to", or "belonging to" in the sense of "idiosyncratic" in relation to the originating matrix. Eigen values and Eigenvectors have many applications in both pure and applied mathematics. They are used in matrix factorization, in quantum mechanics, and in many other areas.

Eigenvectors and Eigen values of a real matrix

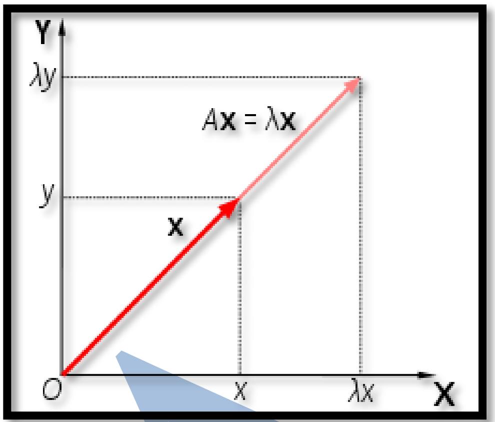


FIG. 6. Matrix Aacts by stretching the vector x, not changing its direction, so $x$is an Eigenvector of A.

In many contexts, a vector can be assumed to be a list of real numbers (called *coordinates*), written vertically with brackets around the entire list, such as the vectors *u* and *v* below. Two vectors are said to be scalar multiples of each other (also called parallel or collinear) if they have the same number of coordinates, and if every coordinate of one vector is obtained by multiplying each corresponding coordinate in the other vector by the same number (known as a *scaling factor*, or a *scalar*). For example, the vectors

$$u = \begin{bmatrix}1\\3\\4\end{bmatrix} \text{ and } v = \begin{bmatrix}-20\\-60\\-80\end{bmatrix}$$

are scalar multiples of each other, because each coordinate of $v$is -20 times the corresponding coordinate of u. A vector with three coordinates, like $u$or $v$above, may represent a point in three-dimensional space, relative to some Cartesian coordinate system. It helps to think of such a vector as the tip of an arrow whose tail is at the origin of the coordinate system. In this case, the condition "u is parallel to v" means that the two arrows lie on the same straight line, and may differ only in length and direction along that line. If we multiply any square matrix $A$with $n$rows and $n$columns by such a vector v, the result will be another vector $w = Av$, also with $n$rows and one column. That is,

$$\begin{bmatrix}v_1\\v_2\\\vdots\\v_n\end{bmatrix} \text{is mapped to} \begin{bmatrix}w_1\\w_2\\\vdots\\w_n\end{bmatrix} = \begin{bmatrix}A_{1,1} & A_{1,2} & \dots & A_{1,n}\\A_{2,1} & A_{2,2} & \dots & A_{2,n}\\\vdots & \vdots & \ddots & \vdots\\A_{n,1} & A_{n,2} & \dots & A_{n,n}\end{bmatrix}\begin{bmatrix}v_1\\v_2\\\vdots\\v_n\end{bmatrix}$$

where, for each index i, $w_i = A_{i,1}v_1 + A_{i,2}v_2 + \cdots + A_{i,n}v_n = \sum_{j=1}^{n} A_{i,j}v_j$ In general, if $v_j$are not all zeros, the vectors $v$and Avwill not be parallel. When they *are* parallel (that is, when there is some real number λsuch that $Av = \lambda v$) we say that $v$is an **Eigenvector** of A. In that case, the scale factor $\lambda$is said to be the **Eigen value** corresponding to that Eigenvector.

In particular, multiplication by a 3×3 matrix Amay change both the direction and the magnitude of an arrow $v$in three-dimensional space. However, if $v$is an Eigenvector of A

with Eigen value λ, the operation may only change its length, and either keep its direction or flip it (make the arrow point in the exact opposite direction). Specifically, the length of the arrow will increase if $|\lambda| > 1$, remain the same if $|\lambda| = 1$, and decrease it if $|\lambda| < 1$. Moreover, the direction will be precisely the same if $\lambda > 0$, and flipped if $\lambda < 0$. If $\lambda = 0$, then the length of the arrow becomes zero.

An example

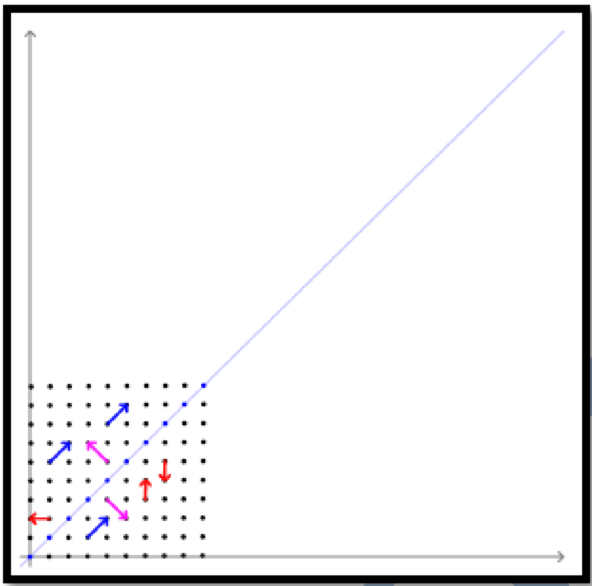


FIG. 8 An example of transformation matrix

The transformation matrix $\begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$ preserves the angle of arrows parallel to the lines from the origin to $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ (in blue) and to $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ (in purple). The points that lie on a line through the origin and an Eigenvector remain on the line after the transformation. The arrows in red are not parallel to such a line, therefore their angle is altered by the transformation. See also: An extended version, showing all four quadrants.

For the transformation matrix

$$A = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix},$$ the vector $$v = \begin{bmatrix} 4 \\ -4 \end{bmatrix}$$

is an Eigenvector with Eigen value 2. Indeed,

$$Av = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} 4 \\ -4 \end{bmatrix} = \begin{bmatrix} 3 \cdot 4 + 1 \cdot (-4) \\ 1 \cdot 4 + 3 \cdot (-4) \end{bmatrix} = \begin{bmatrix} 8 \\ -8 \end{bmatrix} = 2 \cdot \begin{bmatrix} 4 \\ -4 \end{bmatrix}$$

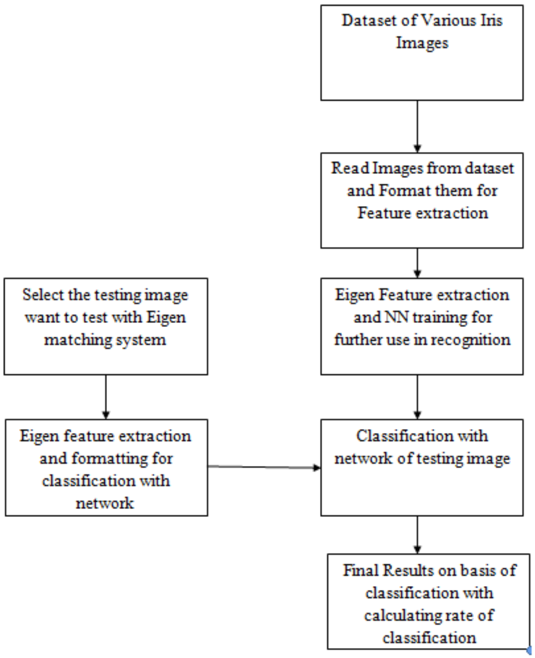
On the other hand the vector

$$v = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$ is *not* an Eigenvector, since

$$\begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \cdot 0 + 1 \cdot 1 \\ 1 \cdot 0 + 3 \cdot 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \end{bmatrix},$$

and this vector is not a multiple of the original vector v. Therefore, the vectors $[1, 0, 0]^T$ and $[0, 0, 1]^T$ are Eigenvectors of A corresponding to the Eigen values 1 and 3 respectively. (Here the symbol ^{T} indicates matrix transposition, in this case turning the row vectors into column vectors.)

FLOW CHART OF PROPOSED WORK



V. CONCLUSIONS & FUTURE SCOPE

To best recognize the iris for biometric security or matching applications our proposed algorithm, is quit efficient as compared with earlier solely working algorithms. We conferred associate improved task programming rule supported the essential Eigen features extraction and database creation algorithms for the task programming in recognition with the achieving the objective of fast detection and accuracy enhanced technology development. The results show that the new methodology based mostly task programming rule not solely may be able to get higher resources utilization, however additionally has the flexibility to accurately recognition task performing capability.

As a future scope many other matching or feature extraction algorithms can be combined with the approach given in this thesis so as to provide some additional feature as rotation less matching. Overall conclusion is that our proposed work is effective and less time consuming and providing better recognition rate with respect to traditional approaches.

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