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Ear Pattern Recognition and Compression using SURF and SVM

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ABSTRACT: Biometric can be defined as the set of methods which are used to measure the physical and behavioral traits of a person for identification and verification. There are several application areas where biometrics can be used. There are two types of application: identification or recognition and authentication or verification. In this paper for Recognition, Ear pattern is used. It is a biometric used for human identification in which PCA is used. PCA is an ear image compression technique, in which eigen ears are preferred. The features are extraction using the PCA technique. And after feature extraction, the recognition is performed on these features to recognize the individual. SVM classifier is a classifier which is used in this paper for performing the recognition function and SURF is used for matching the input image with the database and comparison is done between the previous and the proposed approach on the basis of results obtained after matching.

KEYWORDS: recognition, PCA, biometric, SURF, compression, SVM

I. INTRODUCTION

Biometric consists of set of techniques generally used to estimate the physical as well as behavioural traits of an individual for identification and authentication of a person. Physical biometrics involve face recognition, retina scan and iris scan, hand print and all of these biometrics are very common and accessible than behavioural biometrics. which involve hand writing, signature, typing pattern and gait recognition.

Both Physical and Behavioural methods are further divided into two types; invasive and non-invasive. In invasive technique we require cooperation from the user to attain the information which is required for the comparison of feature extracted with the information already stored in the database, whereas in non-invasive technique there is no requirement of any user cooperation because the information is obtained without informing anything about our work and the subject does not realize anything about it. The biometric systems are most pertinent in security, robotics, and medical aspirations. In such fields face recognition, iris scan, retina scan and finger print can be used.

Hand print, retina scan, iris scan and finger print scanning all comes under the category of invasive method, which are not applicable in some areas for example surveillance because finger print scanning or iris scanning require high quality cameras and scanners so as to extract good quality images whereas face and gait recognition comes under the non-invasive methods because they don’t need high quality cameras. Similarly the ear pattern and face pattern recognition comes under non-invasive method. In the ear pattern recognition we can use the same camera which is utilised for the recognition through face biometric. The researchers gave a slightest scrutiny towards the recognition through ear patterns rather than other biometric techniques.

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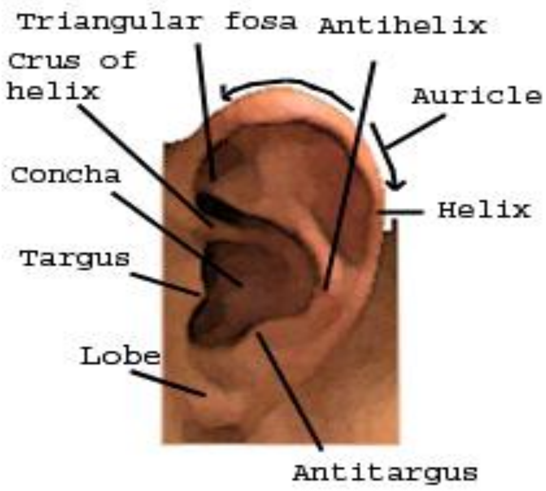

Fig 1: Structure of the external ear

In early years some researchers have started considering the complication related to computations of ear image recognition. The research show that ear pattern recognition is pertinent to a great extent.

II. RELATED WORK

In "A survey on Ear Biometrics" [1] the authors considered two main stages of an ear recognition system: first is the detection stage and second is the features used for recognition. The current ear detection and recognition systems have reached a certain level of ability.

The researches done in the previous years gave us the idea use the ear for human identification [2]. Researchers have advocated that the anatomy of outer ear seems different for each person and it does not change throughout the ages. Although nobody has proved that ear of every human being is different, studies in [12], [13] gave supported evidence to it.

The French criminologist Alphonse Bertillon was the first who gave the idea the using the ears for identification more than 100 years ago [11]. A lot of researches has been made to specify that the anatomy of outer ear is different and not change by increasing in age. While it has not been proved that every person ears are different. But in [10] it gives a supporting evidence. Iannarelli [12] work was very prominent in this field who examined more than 10,000 ears. By undergoing to some procedure found that all of them are different. Iannarelli developed an anthropometric method in which he used 12 measurements to distinguish the human beings depending on their ear images. Later in 1995 Carreira-Perpinan [19] gave a contribution to research by using artificial neural network linear nodes used for feature extraction. Because of linear nodes, that was very little bit difference in singular value decomposition and the decision rule was made by exceeding the given threshold of reconstruction error. More recently, Chang et al. [17] gave a comparison between face recognition and ear image matching using a standard principal component analysis known as Eigen faces approach for face recognition and ear images acquired at university of south Florida. They reported that there is a very little bit difference in recognition performance for the two methods face recognition and ear recognition. The performances were registered 71.6% and 70.5% for ear and face recognition respectively. The given accuracies obtained in the baseline experiment. Chang *et al*. Also depicted effects of lightening variation experiment which reported in the result were 64.9% for face recognition and 68.5% for ear recognition. In the multimodal experiment which is used for combining face and ear images. They concluded that the reporting rates are increased by using both the two methods for combination and our result got explored to 90.9% increased by combining both the image methods together.[35] p proposed a novel 3D ear recognition approach. Experimental results indicate that the proposed method could achieve high ear detection rate, high identification accuracy and low computational cost

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III.RESEARCH METHODOLOGY

The methodology which is followed in this paper use mathematical modelling for position estimation and use MATLAB as simulation tool to analyze the performance of the proposed approach and to obtain the comparison with all the existing methods. In this method a training dataset and testing dataset of ear images is used. The compression of image or dimensionality reduction of image is obtained after embellishing image by removing the noise. The basic methodology flow chart is shown in Fig 1 below:

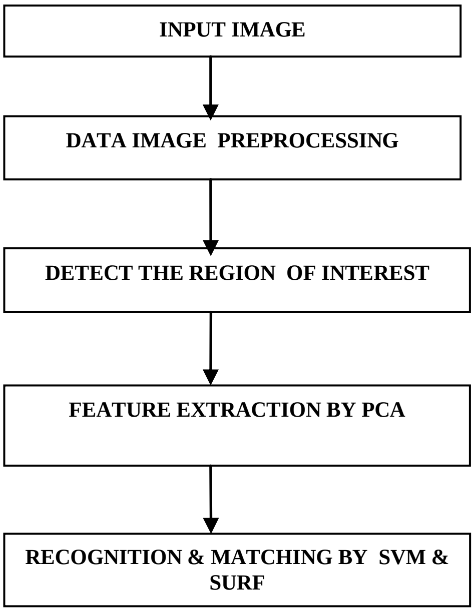

Fig 2: Flow Chart

A. Pre-processing

In the pre-processing step, conversion is done from the image to grey scale, and then histogram equalization, and Gaussian filtering is performed. This step is imperative for the noise removal and for image smoothening.

A.1 Conversion to grey scale:

This involves mapping colour RGB triplets into a single value which represents the grey scale intensity. Each colour pixel is described by the intensities for red, green, and blue.
A weighted average of these values is estimated as the grey scale intensity as shown below:

$$I=0.21R+0.72G+0.07B$$

A weighted average is used for human recognition. Humans are more susceptible to green than other colours therefore green coloUr carries the largest weight as compared to red and blue.

A.2 Histogram Equalization:

This involves transformation of the histogram of image so as to increase the contrast. The intensities will be uniformly distributed on the histogram.
A.3 Gaussian filtering

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Filtering in the pre-processing is done to reduce noise. Gaussian Filtering is used to reduce the noise in the images by minimizing the intensity variation among the pixels. It uses a 2D sliding window matrix (kernel) that gradually traverses the image and utilises the values of pixel contained in the sliding window to replace the value of centre pixel.

The equation used for the Gaussian function is:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2x\sigma^2}}$$

This function is used to set values of the sliding window and performs the sum of products.

B. Feature Extraction

Feature extraction deals with isolating distinct features of the ear in the image. PCA method is used for the extraction of features for image.

B.1 Principal Component Analysis (PCA)

In this approach, firstly the principal components is obtained and then these components are used as transformation matrix for the transformation of training set images and test images to PCA space

Each and every pixels of an image are taken row by row from top to bottom and then they again converted to row vector which contain the intensity values or grey scale of that image. By concatenating these row vectors a single matrix is transformed. Every image is depicted by row in that matrix. Two separate matrices are transformed for test image set and training image set. Both the training and test images are undergone this same process.

After this the covariance matrix is calculated for training set images in which image is depicted by each row and pixel position is depicted by columns. Covariance between two variables will be positive if both the variables vary above their expected value but if one varies above its expected value and second diversify below its expected value then there will be negative covariance. For calculating the covariance;

$$Cov(x_i, x_j) = E\left[\left(x_i - \mu_i\right)\left(x_j \mu_j\right)\right]$$

$$(for\ i\ and\ j = 1,2,3 \ldots \ldots n)$$

where E is the mathematical expression and $\mu_i = Ex_i$, and x is training image matrix. If the order of matrix x is (*m* x *n*), where n represents columns for number of pixels per image and m represents rows to represent number of images. Then the order of new resulted covariance matrix is (*n* x *n*).

Transformation to the PCA space: The resulting matrix *A* is formed by sorting the eigenvectors used as a transformation matrix to transform the images to the PCA space. This is done by substituting the values in the formula given below;

$$Y = A(p - m_x)^t$$

Where P expresses a vector representing image and m_x states the mean value of each pixel position of all training set images. The calculated vector *y* is the image which is transformed to PCA space. That is defined as *principal component transform.* Now all the images in the training set are transformed into the PCA space. With the help of the above transformation, we consider a new test image *t* which helps us in identification of training set. Same transformation is applied to test image.

$$r = A(T - m_x)^t$$

The vector *r* is the mapping of that image to the PCA space.

Dimensionality reduction: The size of eigenvector matrix is (*n* x *n*), we concludes that there are n eigenvectors (where n is the number of pixel per image) and by transformation to PCA space we got a n dimensional space. To compress that space, its dimensionality has to be decreased or reduced and for this we can take the top k eigenvectors corresponding to top k highest eigen values which will help in transforming matrix A_k. Calculate the size of the transformation matrix.

$$K = \lfloor number\ of\ pixel/2 \rfloor$$

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For example, suppose the size of an image in the database is 70×40 that is there are 2800 pixels per image. After the transformation to PCA space and the reduction in dimensionality, the size of the image of new reduced transformation matrix, will approx 1400 pixel per image which is half of 2800.
This is the main process that is pursued in all the experiments where PCA transformation is used.

C. Recognition

Recognition is the final act of classifying an ear image as belonging to a certain individual. It involves using the set of features that were extracted and comparing them to the database to determine which image matches the closest to it. Recognition is done using support vector machine (SVM).

C.1 Support Vector Machine (SVM)

SVM is a classification method which was introduced by Vapnik in the year 1992. This classifier is mainly used in bioinformatics and other disciplines due to its many advantages like highly accurate, can process the high-dimensional data such as gene expression. It belongs to the general category of kernel methods. A kernel method depends on the data obtained through dot-products. In this case, kernel function is used which computes a dot product in possibly high dimensional feature space. There are two advantages
First, it has the ability to generate non-linear decision boundaries.
Second, by using kernel functions the user is allowed to apply a classifier to data with no obvious fixed-dimensional vector space representation, examples of such data in bioinformatics are sequence, either DNA or protein, and protein structure, etc.
The main aim is to provide the user with an instinctive understanding of the choices regarding which kernel is to be used and provide guidelines related to general usage. SVM has been used successfully in many real-world problems like gait recognition, text categorization, image classification, bioinformatics i.e. for Protein classification, Cancer classification etc. And SVM has its successful application in hand-written character recognition.

D. Matching

Surf is used in various systems for performing matching operation. It is a robust local feature detector and is good at handling images with rotation and blurring. But it is not good at handling viewpoint and illumination changes. Analysis shows that SIFT is three times slower than SURF. It approximates the schemes which are previously proposed with respect to uniqueness, repeatability, and robustness and yet can be computed and compared much faster as compared with other matching techniques.

IV.EXPERIMENTAL RESULTS

In this section, we perform experiments to prove the adequacy of the proposed approach. The comparison of the PSNR, MSE, Entropy and BER is done with the given values to the proposed work. Fig 3 shows all the graphs for estimated PSNR, MSE, Entropy and the BER and Fig 4 shows the graph for estimated Recognition Rate in the proposed approach. This shows that the proposed system is much efficient as compared with the previous system. All the parameters are calculated just to verify the efficacy of the system.

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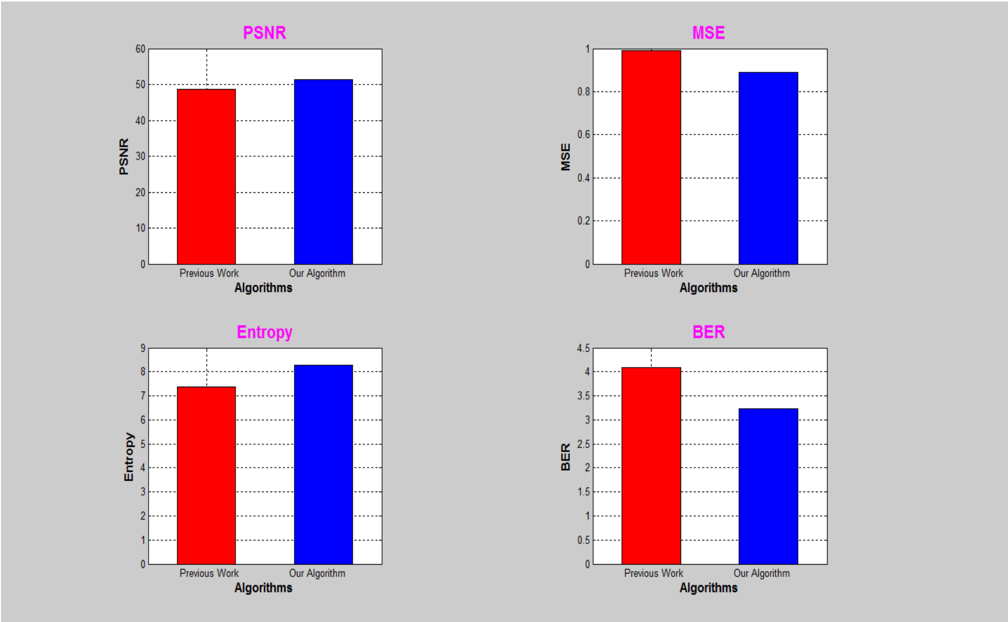

Fig 3 PSNR, MSE, Entropy and BER graphs

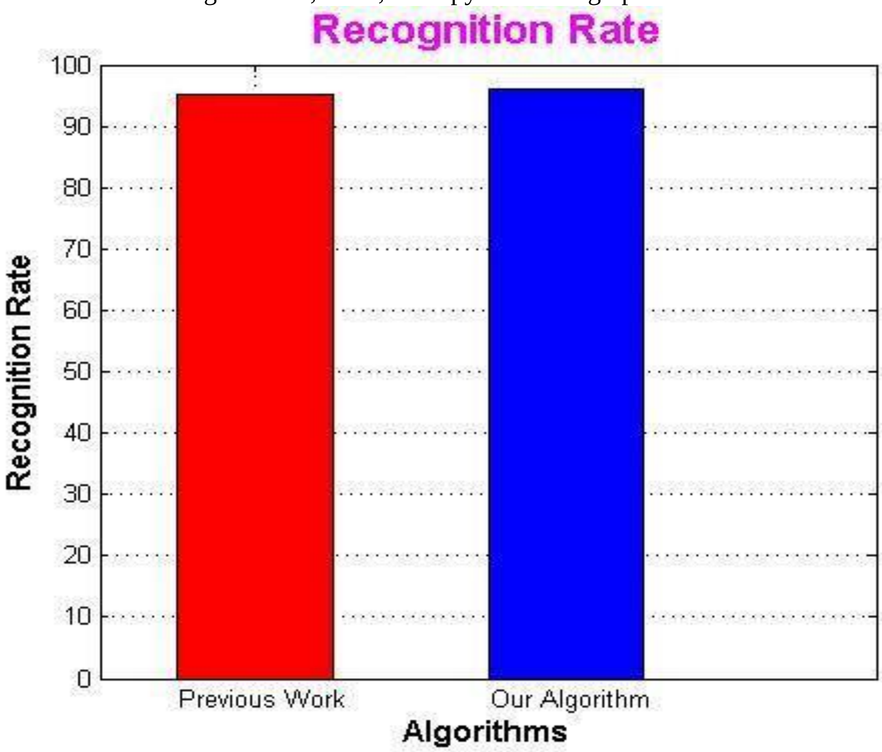

Fig 4 Recognition Rate graph

	Previous Work	Proposed Work
BER	4.0900	3.2349
ENTROPY	7.3582	8.2793
MSE	0.9890	0.8877
PSNR	48.5900	51.3056

Fig 5 Comparison between previous and proposed approach

Comparison of Recognition Rate between Previous and our algorithm

	Previous Work	Proposed Work
Recognition Rate	95.2300	96.0656

Fig 6 Comparison between Recognition Rate between previous and our algorithm

Fig 4 shows the comparison between all the parameters of both previous and proposed approaches. This shows that the approach which is proposed in this paper is a better approach than that of previous.
The approach which is proposed in this paper is more decisive and potent when compared with the previous used technique.

III. CONCLUSION

Image restoration processes consist of a collection of techniques. With the increasing demands of visual surveillance systems, human identification at a distance has recently gained more interest. Ear is a potential behavioral feature and many allied studies have demonstrated that it has a rich potential as a biometric for recognition. This thesis has described a simple but effective method for automatic person recognition from Ear. Ear pattern recognition and compression concludes that the values by using parameters PSNR,Recognition Rate MSE, BER and entropy is giving better results than the previous base paper results. The results are better and with increasing efficiency and error free. Although accomplished under some simplified assumptions like previous work, this work has been proven to be an encouraging progress to ear pattern recognition.

IV. FUTURE SCOPE

This thesis is limited to acquiring or retrieving single image from group of database images .We can extend our research work on the different images or more than one image simultaneously. Also in future more parameters like by enhancing the number of pixels quality can be considered. We can further apply new formulas or algorithm for the feature extraction and recognition to enhance the accuracy.
Even though current ear detection and recognition systems have reached a certain level of maturity, their success is limited to controlled indoor conditions. For example, to the best of our knowledge, ear biometrics has yet to be tested outdoors. In addition to variation in brightness, there are other open research issues which involve obstructions due to hair, ear symmetry, ear classification, ear print forensics and ear individuality.

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