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# Wavelet Transformation and Hidden Markov Model in Features Extraction of Ear Images with Occlusion for Human Identification

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**ABSTRACT**: The ear has rich structural features which often don't change during age increasing and with changes of facial expressions. These features also can be used as a biometrical method, without any direct connection with target. Although an efficient function is achieved by existing ear identification methods under controlled situation but it has decreased because of some destructive factors such as occlusion in the human identification accuracy. The main propose Of this article is presenting a new way to dominance on limitations resulted by the occlusion of images. Hidden Markov model, wavelet components and their statistical control are used. In feature extraction, a 3-layer neural network, a 3 layer Layer neural network is used to mate each image with related people's identification tag. In addition we used nearest neighbour method in feature vector to allocate images to real or fake individuals in purpose of being able on comparing 2 different identification comparative methods. USTB database including 308 images (4 image for each person), is used in order to reaching the best rate of accuracy.

**KEYWORDS:** wavelet transformation, Two-Dimensional, ear recognition images, three layer neural network, hidden Markov model.

## I.INTRODUCTION

Human ear contains a great volume of information and unique features which are different even in twins. Birth time and resistant to ageing and environmental effects the main advantage of using ear for human Identification is its form Constancy. Also in this method there is no need of subject's cooperation or no direct touch required, so in such places as airports where human identification is done by fingerprinting or faces and requires person's cooperation and could be construed as an insult, we can save their ear information without their awareness. In addition for wariness. Ear the colour Distribution is monotone so when its colour-photo changes to grey almost all of the information can be saved. Simple and predictable background of ear is it's another precedence to face, because ears exist in 2 sides of head but in face identification photos should be taken in front of a controlled background[1]. Digital photography system are less-expensive, faster and more available in compare to 3-dimensional scanners and 2-D photography can be used as an imperceptible tool[2]. So using 2-D image of human ear is suggested. In pervious works a multi-class program which could distinguish. The best sub window and use it for adjustment was suggested for the ear identification with occlusion of some. Images Nanni and Lumini (2007) presented a multi-adjustment system that could do adjustments by feature so Could do adjustments by feature extracting from a two-dimensional picture. Features were extracted by convolve of each sub window with filter Gabor bank, and then the dimension of vectors decreases by Laplacian .Best adjustment is related to the best sub window in terms of information.[3].Yuan and Mu (2012)used compound method to take 28 sub classes from 28 sub windows and each sub window was planned for extraction of feature vector[4]. Human identification based on ear images has some disadvantages too, its error percentage isn't low and main has some disadvantages too, its error percentage isn't low and don't have algorithmfor occlusions by hair or ear tag. Don't have algorithm for occlusions hair Ear tag .In this article, our purpose is to present a new powerful technique to extract ear features by wavelet transformation, hidden Markov model and multi-layer neural Network with a low error percentage which doesn't have

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pervious problems and can lead to a totally trusted identification system, Due to it can make the image independent from its occlusions. Markov model with tree-structure will be used in this article to extract statistical features of wavelet transformation components. Markov model has a superiority of extracting the information Of image patterns which can lead to a good accuracy of ear feature extraction[5], In order to feature extraction for the pixels of an area or classes, a specified distribution will be assumed $f(x_r|c)$and then matching will be checked by a 3-layer neural network.In addition to be sure of system's proper function we have parallel use of nearest neighbour method, Euclidean, Manhattan and Murkowski's elements. Two main parts in the inspected algorithm used in this article are: 1-feature extraction 2-identification according to patterns. Feature extraction will be done via wavelet transformation. And hidden Markov Model Identification and adjustment of extracted features will be done by 3-layer neural pattern. Therefor the method of this study is mainly consist of 2 phases (1. training 2.Testing) although both of these 2 phases Contain feature extraction But3-layer neural network is educated according to extracted features and during the first phase and then it's been used for recognizing the feature vector related to checking image in the second phase.USTB is the used database of this article which includes 308 images of 4 different persons. Figure 1 is shown this samples.

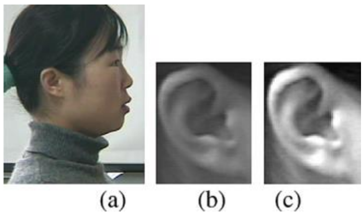


Fig 1: ear identification and normalization (a) original image (b) extracted area (c) ear normalized image

## II.RELATED WORKS DONE FOR DOMINATING OCCLUSION PROBLEM

Arbab-Zavar and his cohorts, (2007) used SIFT constant scale conversion to detect the features of ear images. They took Photos from right side of individuals' heads, recorded identified ear images were chosen by a model. Prominence of their presented model was compared to components principal analysis (PCA) method. And its prominence in detecting the effectiveness and its prominence in detecting the effectiveness of occlusion problem was investigated. [6]after them were Bustard and Nixon(2008) have studied occlusion of upper parts of images but other areas such as central or lower parts not analysed [7]Yuan and chun Mu(2012) presented some identifications of images from database which had brief occlusion on the ear form by 2-D image recognition method based on local information. Each 2-D image was each 2-D Image was divided to sub windows then contrived neighbours were used to extract each sub window. A sub class is defined in order to choosing the best sub window. According to experimental results in USTB and UND databases, the sub windows method can help us to identify the best ear areas in the future. Extracted results are related to data with a occlusion of 33%in sides and 50% first grade of identification is related to $24^{th}$ sub class and the 98% rate of accuracy and has a87% rate of accuracy in UND database [4] .Yuan and his cohorts (2016) introduced an occlusion analyser for codification of occluded areas on image. Exhibiting dispersion based on classification can show a functional way to identifying ear under occlusion. A great amount of the points of occlusion normal analyser with showing dispersion classification (SRC) are with Gabor feature analyses. Codification of coefficients and greatest amount of dispersion was considered. This work showed the showed the increase of identification power. Experimental results on the third collection of the USTB database which includes images containing normal occlusions Identification rate of 100% is reported for an image without any occlusion and the 93.8%, 85.4%, 79.2% are reported for occlusion of 15%, 25%, and 35%[8]

## III.METHOD

As you can see in diagram block of figure (2) for feature extraction during considered mechanism, At first we have to divide images taken from USTB database to 2 training and test groups (in this study 60% of image are used for training, 20% for testing and 20% for validation) So we extract feature vectors related to each image by using wavelet transformation strategy and HMM After considering a 3 layer Neural pattern and a tag for each feature vector, we can train considered 3 layer neural pattern based on feature vectors and tags. Test images will be first taken to feature Test images will be first taken to feature extraction block and be processed by wavelet transformation and HMM and finally given to educated 3 layer neural pattern. The outputs of neural pattern are identification tags which are recognized based

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On training phase.

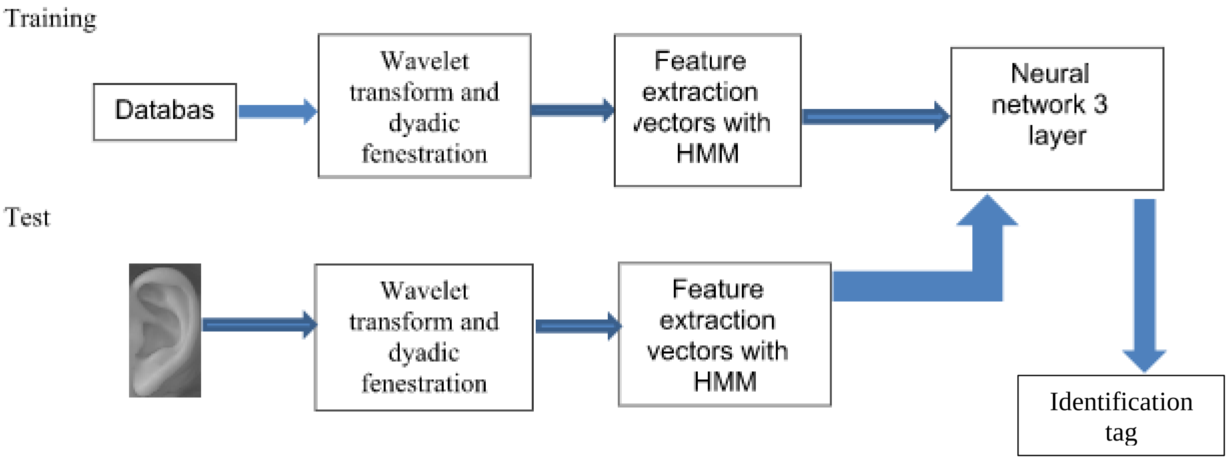


Fig 2: Diagram Block of proposed method

## IV.WAVELET TRANSFORM AND DYADIC FENESTRATION

Wavelet transformation has the ability to divulge special and important features of images .Also modelling its components is easier in compare to original pixels. In addition using tree fenestration structure and wavelet transformation caused highest level of function in human identification. In this study we have focused on simplest type of wavelet transformation which will be done based on the Harr wavelet[9].

Creating wavelet components for an image can be done by four 2-D wavelet filters. These 4 filters are defined as:

1. Local leveller filter:

$$h_{LL} = \frac{1}{2}\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \qquad (1\text{-}4)$$

2. Horizontal edge detector filter

$$g_{LH} = \frac{1}{2}\begin{pmatrix} 1 & 1 \\ -1 & -1 \end{pmatrix} \qquad (2\text{-}4)$$

3. Vertical detector filter

$$g_{HL} = \frac{1}{2}\begin{pmatrix} 1 & -1 \\ 1 & -1 \end{pmatrix} \qquad (3\text{-}4)$$

4. Diagonal edge detector filter

$$g_{HH} = \frac{1}{2}\begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix} \qquad (4\text{-}4)$$

Wavelet transformation divides image to 4 images with half dimension so that images information disports too. LL is the original image that changes to half in each step. HL contains horizontal information of image, LH contains vertical information. And other information which are called diagonal information are in HH.For calculating the wavelet for Calculating the wavelet transformation of one digital image. $2^J \times 2^J$at first produce U matrix by following equation (5-4):

$$U_J[k, l] = x[k, l], \;\; 0 \le k, l \le 2^J - 1 \;\; (5\text{-}4)$$

Then extracted $U_J$matrix have to be convolve by considered wavelet filters and dispose other samples in both K and l direction. Sub band extracted images are shown as: $u_{J-1}$ , $w_{J-1}^{LH}$ , $w_{J-1}^{HL}$ , $w_{J-1}^{HH}$ and each image has the dimension $2^{J-1} \times 2^{J-1}$often results are saved in one matrix$2^J \times 2^J$ as in (6-4)

$$\begin{bmatrix} U_{J-1} & w_{J-1}^{HL} \\ w_{J-1}^{LH} & w_{J-1}^{HH} \end{bmatrix} \qquad (6\text{-}4) \qquad u_j , 0 \le j \le J-1 \;\; (7\text{-}4)$$

With (7-4) condition, filtering process on the $U_{J-1}$image repeats for J times.

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Matrixes of wavelet factors$w_j^{HH}, w_j^{HL}, w_j^{LH}$ are related to the filters of high frequency-horizontal and vertical detected edges-and diagonal directions edges [B] wavelet coefficient$w_{J-1}^{LH}[k,l], 0 \leq k,l \leq 2^{J-1}-1$ for example, if the blocked 2x2 window of an image be included of horizontal edges, will have a great amount. For following 2x2 blocked window The matrix (8-4) will be resulted. Repetitive calculation of each on of wavelet factors related to a 2x2 blocked image cusses a tree structure with 4 parts on the wavelet factors in each sub band.

$$\begin{bmatrix} x[2k,2l] & x[2k,2l+1] \\ x[2k+1,2l] & x[2k+1,2l+1] \end{bmatrix} \quad (8\text{-}4)$$

## V.STRUCTURE OF DATA EXRACTION FROM INVESTGATED IMAGES

According to distribution of various classes' pixels, extraction process $f(x_r|c); c = 1,2,\ldots,N_c$can be done step by step and based on a window with specific size. So as we can investigate the appertain of each window pixels to a class, and choosing the size of the window can be so important. If we use large sized windows during the process data structure will be showed more appropriate, since the number of investigating pixels will increase and better statistical information can be reached, but it also increases the risk of existence of pixels which are related to another class in the window. So although bigger window can cause better features in big and homogeneous areas but it also may cause loss of information in borderline areas in different parts so choosing smaller windows will decrease the probability of existence of pixels from other classes in the window.

So using smaller windows seems more appropriate between the areas and bigger windows can be used in other situations. We have used dyadic blocks idea in order to choose windows for feature extraction then we have divided selected windows to 4 sub parts in every step, this tree structure is shown in figure 3.

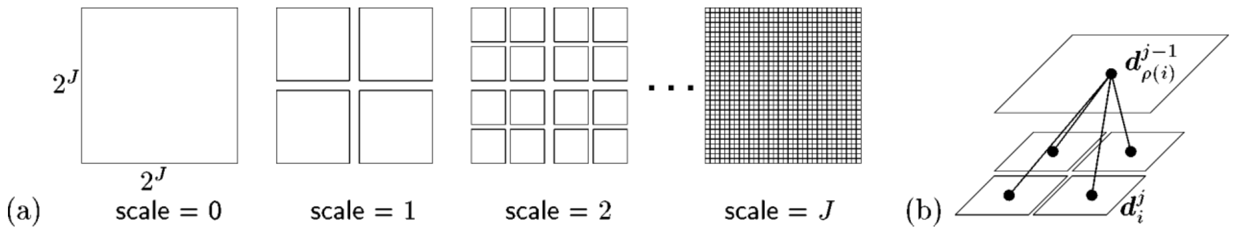


Fig 3: tree structure of scale windows (a) node parents and next generation (b)

In this figure i is the number of squared sub windows in each of scales and J is scale indicator. Also productive sub windows of secondary squared windows are show by p (i) One noticeable point is the wavelet transformation and wavelet statistical model.[10] In feature extraction it's very important to have models with various patterns because it's difficult it's to reach a complete and appropriate pixel distribution.

In this study recognition of image areas is based on image field transformation by wavelet because this inversion linear transformation causes components which changing their structure to a model is easier. Most of images, especially grey images have a structure (including edges and ridges) which using wavelet transformation causes accuracy in scansion of areas in them. In fact, wavelet transformation functions are a detector for the multi scale edge in this cases which defines the structure of images based on various scales and 3 different direction.

Wavelet transformation causes huge components for the edges and small components for the smooth areas. There are many statistical methods for the transforming the structure of the patterns to a model, and we do it by using hidden Markov model (HMM) in this study [11].Hidden Markov model is used for estimating the statistical amount of edges and for the wavelet components hidden .Modelled fines a variable of hidden state for each wavelet components In order to control them. If they are big or small then marginal distribution of each component is modelled by two Gaussian Distribution In related modellings for Gaussian distribution, great variance is used for big areas and small variance is used for small areas. In fact hidden Markov model extracts constancy of great and small components by using dependence between hidden states in scale changing duration .The method of model extraction done by hidden Markov model is shown in figure 4. Independence of wavelet components in various scales is shown in 3 samples.

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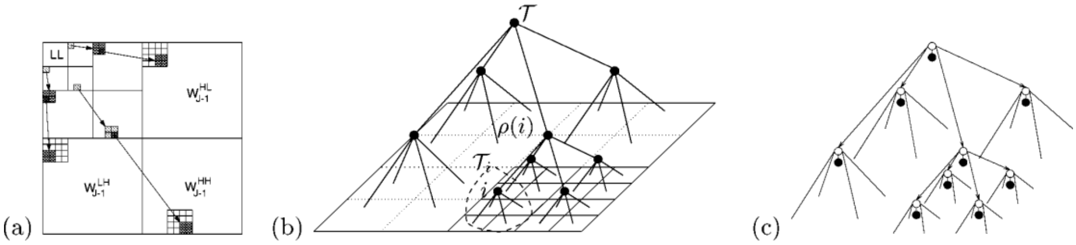


Fig 4: the dependence of wavelet components in different sub bands

In second and third figure 4 wavelet components as black Nods and their connection with sub parts components for a sub band are shown. In third picture white Nods of hidden Markov state variable is for controlling Gaussian model of that Nod.

## VI.CREATING FEATURE VECTORS FROM IMAGE DATA

In each image which is investigating for features extraction, first tree structure fenestration would be created and then wavelet transformation of windows is calculated for feature extraction and then each wavelet component is modelled based on compound of two Gaussian distribution and their variance would be controlled by a hidden Markov state variable[12] In this level we add up the parameters of a model which is compound of 2 Gaussian hybrid variances and the probability of transient Markov state, in M vector.
In this level we add up the parameters of a model which is compound of 2 Gaussian hybrid variances and the So hidden Markov model can be used as a huge amount model (feature vector) for approximation of all wavelet components (w) distribution $\mathrm{f(w|M)}$. It can be used for estimating parameters of hidden Markov model. Tree structure of HMM can make adjustment of windows possible.
Each sub tree related to a HMM tree is a HMM tree too which has started from I Nod and models statistical treatment of wavelet components related to di window. There for we can consider the distribution of each window during modelling process as: $\mathrm{f(d_i|M)}$.
Now we can extract features of images via this tool suppose we have educated a HMM tree based on $\mathrm{M_c}$parameters.For each of pattern classes, now assume wavelet transformation$\tilde{\mathrm{w}}$ of on test image$\tilde{\mathrm{x}}$which includes these patterns.
Calculating the multi scale distribution related to different windows based on each HMM tree cause $\mathrm{f}\left(\tilde{\mathrm{d}}_{\mathrm{i}}\middle|\mathrm{M_c}\right)$ ∈C{1,2,…..,Nc} for each dyadic sub images$\tilde{\mathrm{d}}_{\mathrm{i}}$ (an square, divided to 4 sub part in every step) By having multi scale distributions in this step, feature extraction can be done easily by HMM parameters. Feature extraction process causes a set of different features with J members.$C_j, \mathrm{j} = 0,1, \dots, \mathrm{J} - 1$.

### *A.HMM TREE MODEL OF WAVELET COMPONENT*

A wavelet complete transformation contains 3 sub bands having 3 parallel quadruple tree structures. For example Nod i In LH, HL And HH is from a four part tree which is related to dyadic window di in image. In dependence of sub bands supposition. Three sub bands which are related to wavelet transformation are statistical independent in this state.
Complete M which is HMM tree model of image wavelet components including three HMM tree which are defined as $\mathrm{M} = \{\theta^{\mathrm{LH}}, \theta^{\mathrm{HL}}, \theta^{\mathrm{HH}}\}$. So the tree is a Gaussian combination parameterise model to define dual distribution of wavelet components. In situation of independent sub bands we can have.

$$\mathrm{f(w|M)} = \mathrm{f(w^{LH}|\theta^{LH})f(w^{HL}|\theta^{HL})f(w^{HH}|\theta^{HH})} \qquad (1\text{-}6)$$

## VII.MATCHING AND DECISION

In simulations, feature extraction is considered as resulted model from HMM tree structure and with 24 components (related to distribution parameters and the weight of 3 sub bands) Also 3 layer neural pattern has following topology the Design of neurons in each layer is done by trial and error method and 24 neurons in first layer, 8 neurons in second and 7 neuron in third layer. So we use neural network tool in MATLAB 2011.and we have chosen 60% of data for training network and 20 % for test and 20 % for validation.so we could get the tags of each human who selected for identification.

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This tool is shown in figure 5.

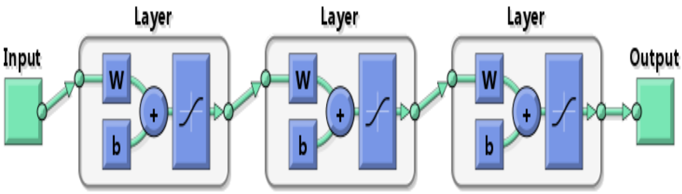


Fig 5 : three layer perspetron neural network.

### *A.ALLICATING AND TESTING OF ONE PERSON'S IMAGES IN COMPARING TO OTHERS*

In one real application, the biometric adjustment is done by a real attempt. (Enrol attempt) and an unreal attempt (an imposter) this experiment will have two kinds of error, it maybe does a mistake and accepts the imposter, or does a mistake and rejects enrol attempt.

The percentage of false acceptance FAR. The possibility of imposter acceptance:

FAR= $\frac{\text{number of false acceptance}}{\text{number of imposter}}$ (1-7)

The percentage of false rejection FRR. The probability of an enrol rejection.

FRR= $\frac{\text{number of false rejection}}{\text{number of enroll attempts}}$ (2-7)

In most biometric systems there is a few FRR that isn't so important because. It's possible that imposter don't be accepted. But the FAR percentage has a special importance in most of biometrical systems. Because there is the probability of choosing an imposter instead of an original attempt. We can find a threshold for dividing system function. Mainly other parameters are used in FRR and FAR mistakes assessment too. In these parameters the rate of EER mistakes defined and finally the general acceptance rate (GAR) of one biometric system is defined as added grades of one threshold. The performance of system is investigated by the changes of FAR and GAR factors in thresholds. These two factors show the GAR parameters against FAR parameters of different thresholds in one curve that called ROC .General acceptance rate (GAR) of a biometrical system is defined as the rate of increased grades from one threshold. Allocating between general and imposter images can be one of them as a general image and one of them as a imposter image.so according to features extraction vectors the nearest distances method is suggested to allocate and investigated parameters. In following you can see three formula about this method.[13]

$d_{cb} = \sum_{j=1}^{n} |x_{sj} - y_{sj}|)$ (3-7)

$d_{ec} = \sqrt{(x_s - y_t)(x_s - y_t)'})$ (3-8)

$d_{mk} = \sqrt[P]{\sum_{j=1}^{N} |x_{sj} - y_{sj}|})$ (3-9)

In (3-7), (3-8), (3-9) $x_s, y_t$are 2 feature vectors assessed by Minkowski$d_{mk}$, city block$d_{cb}$and Euclidean$d_{ec}$ standards. Parameter p is the degree of the Murkowski function which will result the Euclidean scale if p=2. And city block function will be defined if p=1.Now we will be able to extract the threshold point of real or fake persons in image investigating by feature vectors results.

### VIII.ANALYSIS AND EXPERIMENTS IN MULTI LAYER PERSPETRON

At first the trained pattern for the USTB database is appropriate in function or training parameters as it is shown in figure 6 diagram and performance analysis is shown in figure 7.The error of system is assumed as (1-8), (2-8) so that extracted diagrams confirm the function. Trained pattern (Epoch 13) in human identification.

$e_i$=output-$target_i$ (1-8) $mse=mean(e_i{}^2)$ (2-8)

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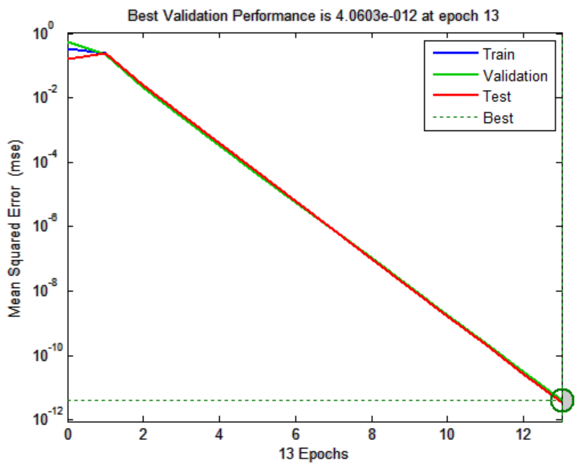


Fig 6: Training parameter

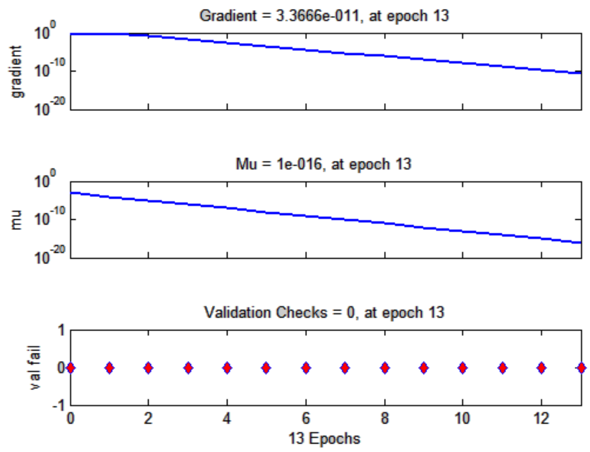


Fig 7: Performance analysis

You can see the gradient decrement for the neural pattern mistaking and preservation of pattern accuracy and adjustment speed in figure 7. In this experiment by loop repetitive testing of neural pattern, it can be realized that the mistaking rate is decreasing after repeating for 13 times and the gradient rate of mistakes decreases during the repetition too. But the speed of identifying identification tags will be lowered too. We check the functional Accuracy during the considered process now. The target is comparison of the function of suggested method to tags declared by database.

***A.ACCURACY SCALE AS AN AVERAGE DUE TO TRAINED NEURAL NETWORK***

The accuracy rate is calculated by: (3-8)

$$Acc = \frac{1}{N}\sum_{i=1}^{N}\delta(\tilde{L}(i), Map_{(L,\tilde{L})}(i))$$

If (a) and (b) be the index collection of all samples enlisted in L and$L^{\sim}$, then the function $Map_{(L,\tilde{L})}$ causes (a) index be adjusted to B. Also $\delta(a,b)$ is the flap function which only in a=b condition takes an amount.

| Wavelet+HMM | ACC (%) |
|---|---|
| RANK 1 | 98.78 |
| Hair Conflicts | 90.43 |

Table 1: Results of accuracy

The experiment of the Accuracy average rate in second part was based on 24 images occluded by hair. These were separately educated to the pattern and resulted an efficient high accuracy rate.

***B.EXPERIMENTAL AND COMPRASSION OF METHODS FOR INVESTIGATION BETWEEN IMPOSTER AND GENIUNE PERSON***

In figure .8 diagram you can consider the human identification by Euclidean space. Which shows a great overlap between genuine and imposter samples. Also you can see this great overlap in figure.9.Related to Minkowski distribution too. However there is a proper threshold or EER% in both experiments. The best resulted distribution for human identification by two-D ear images is related to city block distribution spaces you can see in figure 10.So as we should choose the threshold between minimum to maximum distance and reach the GAR, FAR amounts.

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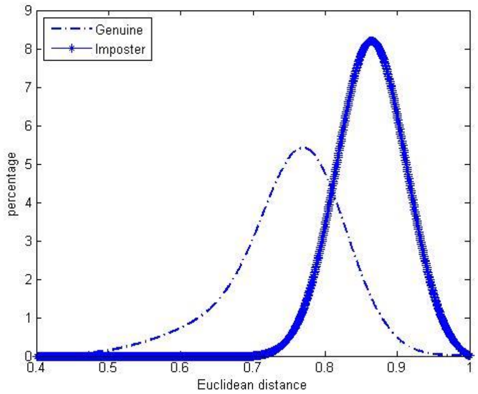


Fig 8: Euclidean Distance

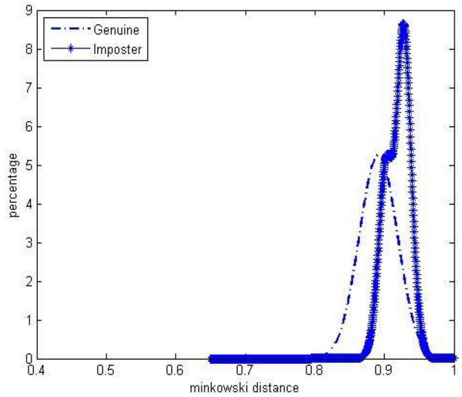


Fig 9: Minkowski distance

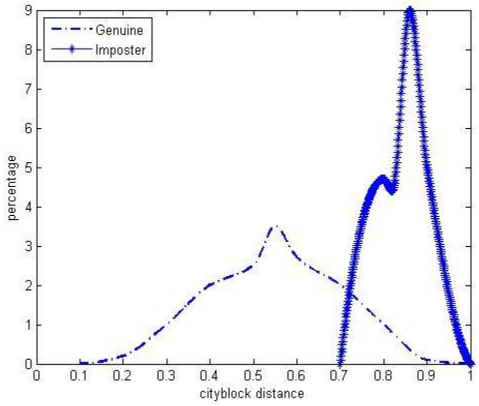


Fig 10: city block distance

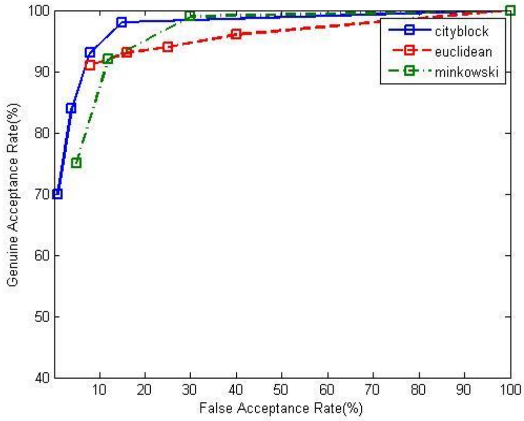


Fig 11: ROC Diagram

The range of selected threshold variations is reached for separation of two Gaussian functions. Which are acquired between minimum and maximum amounts. ROC diagram is for human identification although in this identification appropriate separation ROC diagram. Appropriate separation for city-block function is FAR=9% and GAR=94% but in minckowski and Euclidean methods a very great amount of FAR will cause to a appropriate GAR which identification was not suitable. ROC is shown in figure 11.

***C.IDENTIFICATION TESTING OD OCCLUDED IMAGES BY IMAGE FENESTRATION***

In education phase via wavelet HMM by taking 64 sub classes from 64 sub windows containing dyadic windows, each images is divided to 64 sub windows in J=4. Each sub window will be planned for feature vector extraction. This classifications done by nearest neighbour method. In this step for USTB Database 3 random images were chosen in this Step for USTB Database 3 random images were chosen and tested in order to training and one for testing. These tests were done in 3 different times. And the average amount resulted by this 3 experiment is the final identification rate. This Task Yuan and his cohorts' works [4] the result of experiment shows some parts of ear pattern which can give better information to user. So we can reach the best local information from inner parts of ear and it can be useful in ear identification in those parts which are occluded. Figure 10 shows the increase of identification rate in different sub classes .dyadic fenestration and wavelet transformation can give us the possibility of dividing an image to an appropriate number of sub images**.** Recognition rate for each sub windows could achieve and is shown in figure 12.

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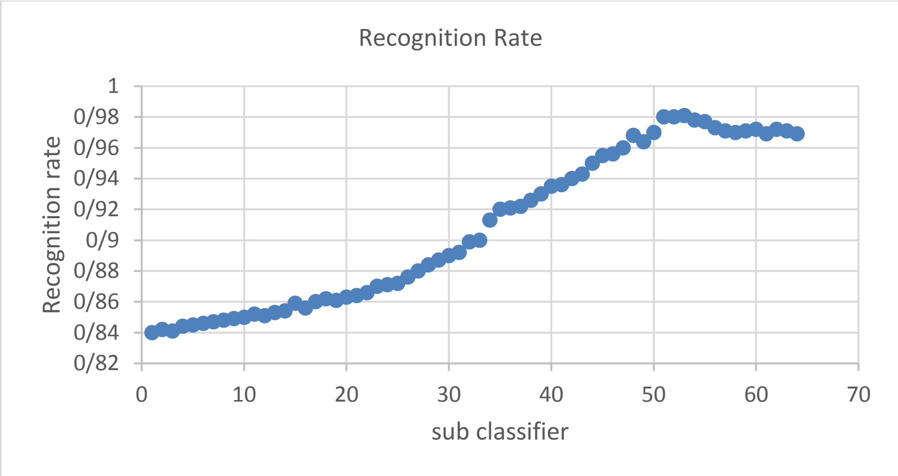


Fig 12:.Recognition rate from fusion information of sub-windows

The rate of final identification with weight on classes in formula $s_k = \sum_{j=1}^{c} w_j s_{jk}$also will achieve. So k is the class number and c number of sub-classifier. So we can take the tag of the class from maximum number $s_k$ a test on ear selected image .figure 13 shows calculations %EER

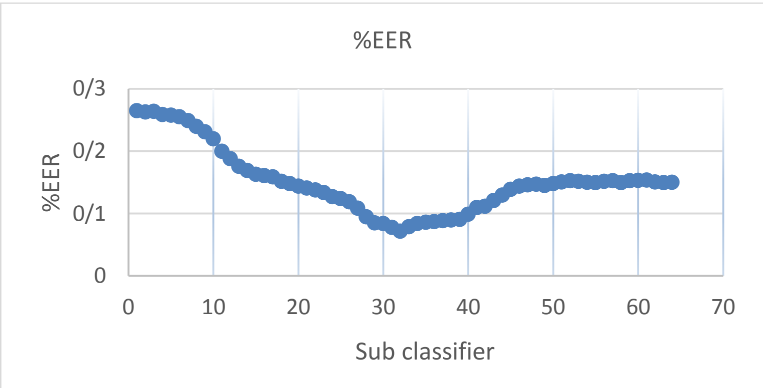


Fig 13:.calculation %EER for sub-classifier

Equations of (4-8), (5-8) shows how can we calculated total recognition rate and EER from sub classifiers.

$w_j = \frac{\text{Rec rate j}}{\sum_{i=1}^{c} rec\, ratei}$ (4-8) EER=$\frac{\%EER}{\sum_{j=1}^{64} \%EER}$ (5-8)

So we decided to product a table after calculate total rates that shows compression between other authors who utilized sub windows so table 2 is provided for shown this compression.

| Person in past | Sub –windows counts | %Recognition rate | %EER |
|---|---|---|---|
| Nanni and lumini[3] | 6 | 96 | 4.3 |
| Yuan, et al[4] | 28 | 98 | 0.08 |
| Proposed method | 64 | 98.78 | 1.9 |

Table 2: compression between sub windows methods and results of them

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## IX. CONCLUSION

There were some problems such as: low identification accuracy rate, inappropriate resolution on images and also the existence of external factors such as occlusion or person's inappropriate or ambiguous images. These problems had somewhat decreased the assurance of using ear biometric for human identification. In this study, we have tried to overcome pervious previous problems by using wavelet transformation and hidden Markov model in feature extraction multi-layer neural pattern and comparing it to traditional methods of classification. As you considered, using multi-layer neural pattern cause a really better identification rate and As experiments show the feature extraction and statistical control can be acceptable even in nearest neighbour method. Occluded images were tested in both network and information compositing method in order to comparing traditional methods at the same time.
In the future, this model can be used for feature extraction of the edges and bulges of 3-D ear images and reaching an efficient classification of information taken by perceptron multi-layer neural pattern.

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