HUMAN EAR CLASSIFICATION SCHEME BASED ON LOBULE CHAIN CODE AND HELIX DIMENSIONALITY

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Abstract

In this paper, a human ear classification approach which uses the ear image contour was proposed. Basically, the scheme has four classification groups which are based on only two concepts namely: Chain code (Lobed and Lobeless Ear) and Dimensionality of Helix (Big and Small Ear). Using the chain code feature vectors extracted from the ear contour after necessary pre-processing activities, the ear were classified based on the code pattern of the last twenty or fifteen codes which uses the rule of thumb classifier we built. Similarly, the second classification process implored the Helix dimensional features which were a product of the Angular Points and landmark space, using the Square of Sum Difference. Therefore, the experimental result showed about 94.80% and 92.20% accuracy respectively.

Keywords: Ear Classification, Contour, Chain code, Lobule and Helix, and Square of Sum Difference

Introduction

The increase in the need for identity authentication to curb security bridges in various areas such as airport, border, surveillance building, and country database have necessitated an exponential increase in the volume of various biometrics trait databases which was kept for this purposes. Thus, due to this increase or anticipated rise of the volume of database, many have started devising various means in dealing with the huge database by providing a classification scheme. Because of the unchanging nature of the ear from birth, (Choraś, 2004), (Zhichun Mu *et al.*, 2004), (Arbab-Zavar and Nixon, 2007), and (Gede Ketut I. *et al.*, 2012) confirmed that the geometric feature of the ear which is a representation of the shape of the ear is more suitable when compared to the texture, colour and the likes. The use of chain code orientation for shape representation involves shape description of contours as in stated by (Sun and Wu, 2007); and (Kirti Jain *et al.*, 2013) which exploits the shape information of an image using chain code. Though the duo complained of the time consumption and noise sensitivity of the method, thus this can only be witnessed in a situation when the entire image is involved with a very poor pre-processing scheme.

Ear Structure

Biometrics is taking a good advantage of the structure of human ear, and its connected pattern has given it a more unique signature which cannot be compromised in anyway. Though it is small, but its interlinked structure ensures that sense of hearing and normal balance are maintained (Irwin, 2006). The human ear is made up three different parts: outer ear, middle ear and the inner ear; and all this parts are interdependent with their functions. The structure of the outer ear helps in guiding sound waves into the middle ear. The middle ear projects the waves to the inner ear with the help of the small bones, while the inner ear ensures that the nerve moves this sound wave to the brain for interpretation. The world of biometrics is majorly concerned with the outer ear also called pinna and it was observed by (Sumalai Maroonroge *et al.*, 2009) that most of anatomical paired structure like Pinna, differs in shape and this is confirmed by the rumbled cartilage on the Pinna which covered the human skin. While the structure of the Pinna enables it to direct sounds toward the ear, the biometric author takes the same structural advantage for identification purposes. (Ximena Wortsman and Jemec, 2008); affirmed that the two distinguishable part of the pinna is the upper (Helix) and lower (Lobule) parts. Anatomically, the upper part can be distinguished with the present or absence of cartilage which contains two third of the pinna, and the lower part has no cartilage and it also consist of skin only. Figure 1 below depicts the different parts of human Pinna.

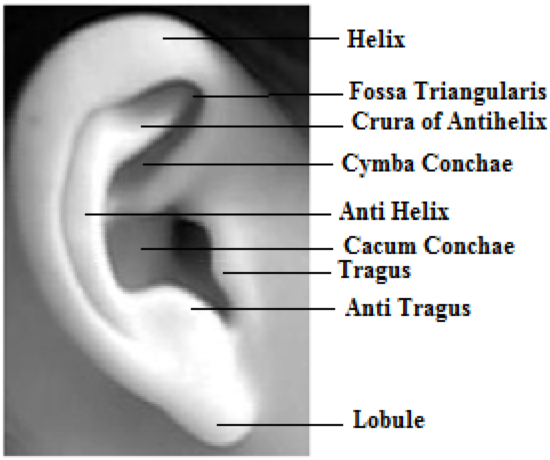


Figure 1: The Anatomy of the Ear

In classifying the ear biometrics trait, the structural nature of the Helix and Lobule are the most distinguishable parts which are likely to be used for the classification process. Study by (Rahman Khosandi and Abdel-Mottaleb, 2013); shows that Gabor filters was used for the extraction of features and the ear was subsequently classified based on gender through the application of sparse representation. Meanwhile, (Guangpeng Zhang and Wang, 2011) used hierarchical and discriminative bag of features technique for feature extraction before imploring SVM which is used in classifying the face profile and ear based on gender.

Methodology:

This section shows a detail work-through of the new approach for ear classification based on chain code signature of the Lobule and the dimensionality of the Helix. The figure 2 below depicts the work flow of the proposed ear classification scheme, which groups the human ear into four different classes namely; Lobed, Lobeless, Big and Small Ear.

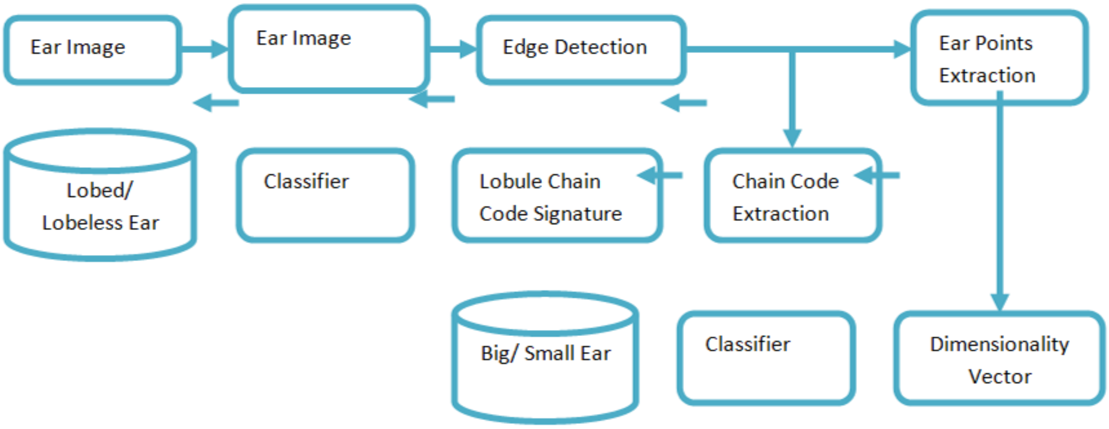


Figure 2: Methodology of the Classification Scheme

Ear Image Pre-Processing:

For a desirable output, the quality of an image plays a crucial role in image processing and image analysis due to the variation of the image. Our pre-processing activities include: Image cropping, Enhancement, Normalization, and Edge detection.

This paper does not show any automatic ear detection approach, but uses a manual cropping technique because of the nature of the ear database used. Since the database has ear images taken from close range, it is believe that the automatic detection approach will constitute time wastage and looking at the fact that there are variations in size of the images, it will not be necessary to have a fixed cropping size for all the ear images. Therefore, cropping the image automatically resizes to a range of 225 x 156 pixels to

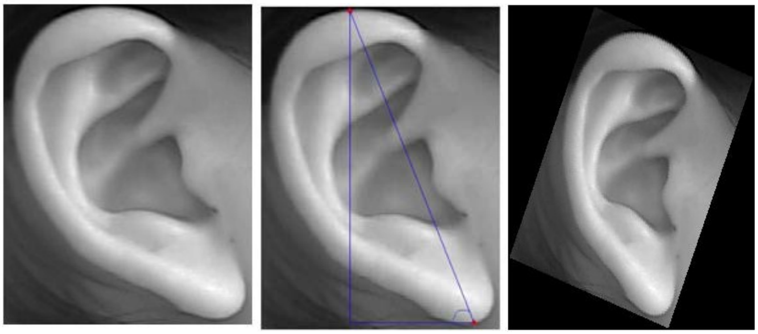
296 x 210 pixels and this helps in reducing the processing activities since less background of the ear image is now available for further analysis.

These cropped images were enhanced depending on their grey scale values to ensure a quality image which cannot be comprised. Though the cropping normalized the image according their various sizes, the image normalization in this section involves the rotation of the ear image so that the landmark is 90 degrees to the plan as shown in figure 3 below. The rotation angle can be calculated using the formula below:

$$\text{Angle} = \operatorname{atan}\left(\frac{x}{y}\right) * 180/\text{PI}$$

$$\text{RotatedAngle} = \text{Angle} - 90$$

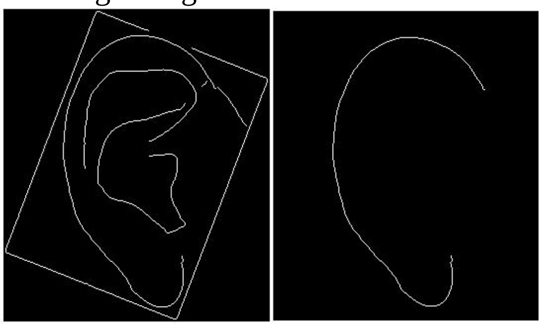
The Rotated Angle gives the actual angle of rotation to ensure that the landmark rotates 90 degrees to the x-plane as in figure 3c.



(a) (b) (c)

Figure 3: (a) Original Ear Image (b) Detection of landmark (c) Normalized Image

After the normalization processing, we used canny edge operator to detect the ear edge image. For efficient usage of this operator to various ear image in the database, it is pertinent to use a sigma with a range of 0.09 – 0.2 towards ensuring a better edge image quality. Figure 4 below shows the detected normalized ear edge image.



(a) (b)

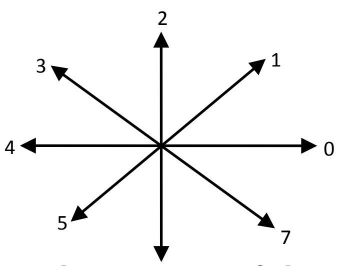
Figure 4: Ear Edge Image. (a) Detected Ear Edge Image (b) Detected Outer Ear Shape

In detecting ear edge image as shown in figure 4a, we were presented with different lengths of edges which we separated by numbering the different connected components, thus thereby detecting the second longest as the outer contour of the ear edge image. This was achieved by first identifying the different connected component and then scan-counting the components pixel by pixel to detect the outer ear edge contour as shown in figure 4b.

Chain Code Signature Extraction

Chain code is basically one of the techniques used in representing the structural shape of an image, and it helps in presenting the image as a series of scanned lines which can be easily stored for image analysis. It was affirmed by (Russ, 2007) that chain code contains shape information which can be used to trace contours, simplify outline shape, match features and even compute various shape descriptor. To be able to capture the chain code signature of the ear edge image, the initial and terminal point of the contour is detected after been left with a single contour representing the outer edge of the ear. The Freeman 8-directional chain code shown in figure 5 was used, starting from the initial point and moves pixel by pixel on the detected contour until the terminal point is met to generate the chain code signature.

Figure 5: 8- Neighbourhood Chain Code



So given a contour C = $\{P0 \ldots \ldots \ldots . Pn\}$

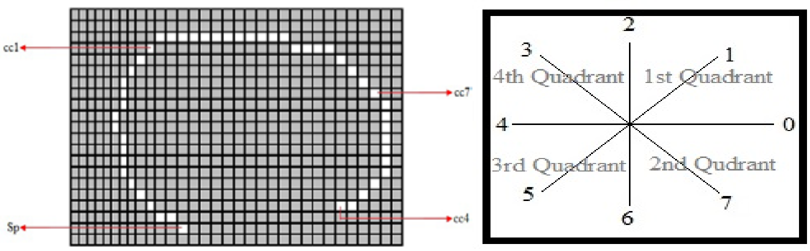
∃ Initial point P0 and terminal point Pn and

P0 ……….. Pn∈ C

Using 8-directional chain code E = $\{E0 \ldots \ldots \ldots . E1\}$

Also $P \in E$ if ∃ link between the pixels in C.

Using this axioms and prototype in figure 6a, the signature of the chain code will be extracted by moving clockwise from the bottom left of contour labelled Sp which is the starting point, to the next pixel and this shift will continue pixel by pixel until the terminal pixel labelled cc4 is attained which is at the bottom right.



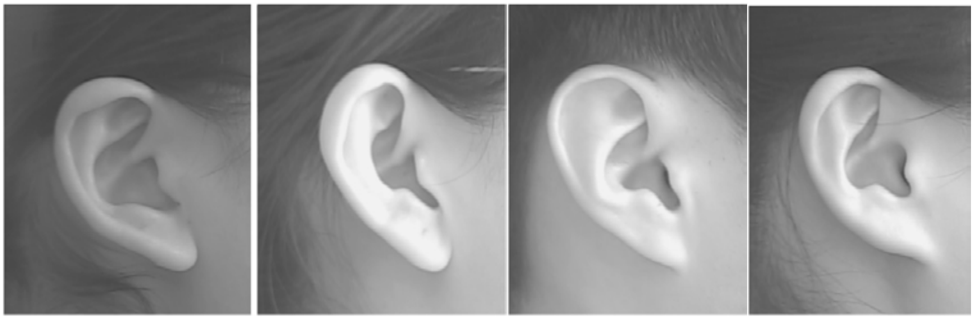
(a) (b)

Figure 6: Analysis Chain Code extraction. (a) Ear Edge pixel grid (b) Chain Code Quadrants

The basic concept of this classification scheme assumes that for an ear edge contour to be conceived as Lobeless, its chain code structure should contain the code which is part of the second quadrant of the freeman-8 neighbourhood chain code with codes 0 and 6 inclusive. While a Lobed ear will contain the second and third quadrant codes with codes 6 and 4 minus code 0. Therefore, having this assumption beforehand makes the scheme more efficient for classification purposes.

Ear Classification Based On The Lobule Structure

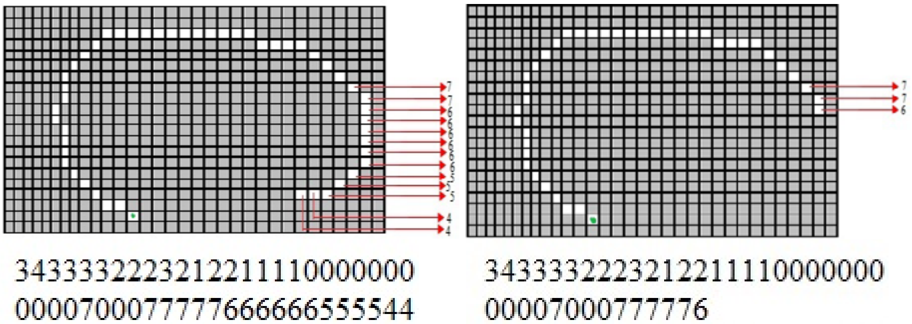
Machine perception is very imperative in machine vision. Thus, if the machine can be able to detect an object or structure, it is obvious that it can also classify them in as much as there is an underlying natural fundamentals which can assist in grouping them. Classification involves designing a criteria which can be applied in distinguishing images or structures; thus, (Russ, 2007) observed that this criteria can vary in form and sophistication depending on the features extracted and on the application area. In our classification scheme, we grouped the ear into Lobeless and Lobed ear. The latter is when the lobule is hanging freely or detached from the head, while the former is when the lobule is attached to the head. The figure 7 depicts two different classes of the ear as mentioned above.



(a) (b) (c) (d)

Figure 7: Lobule shapes. (a and b) Lobed Ear (c and d) Lobeless Ear

Meanwhile, the chain code signature so extracted during the feature extraction stage is for the entire ear contour structure, but our classification scheme utilizes the chain code pattern of Lobule to group the ear into Lobed and Lobeless as shown figure 8.



(a) (b)

Figure 8: Chain Code extraction. (a) Lobed Edge pixel grid and Chain Code Signature (b) Lobeless Edge pixel grid and Chain Code Signature

Scanning the ear edge contour in figure 8a and 8b starting from the green dot at the bottom left using 8-connectivity neighbourhood to the terminal point at the bottom right marked, will produce the chain code signature as shown in figure 8c and figure 8d respectively. Therefore, all these code depends on the direction of the pixel from the previously located pixel.

Orientation-Based Classifier

The classifier model designed in this section makes use of the orientation of the pixels on the Lobule. It was observed that the orientation of the Lobule differs in the two classes of hearing as discussed above. So in the quest for developing a classification scheme, our classification model takes the advantage of the orientation of the edge image at par with the chain code at the lobule to group the ear. This was achieved by scanning the extracted chain code signature at the Lobule, leaving us with fewer chain code signatures which occupy lesser memory, and this vector is subsequently used to classify the ear image with the help of some criteria. This is done by looping through the code signature generated in an anti-clockwise searching for the first fifteen numbers (codes) which contains more or less occurrence of code 7 orientations. Figure 9 below shows the summary of the classification decision flow.

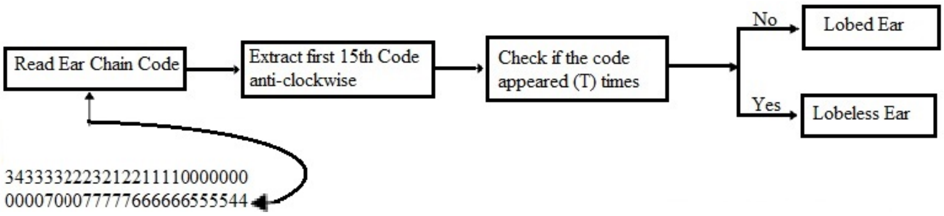


Figure 9: Classification Procedure

Ear Classification Based on the Dimensionality of Helix

Although it might be deceiving to use image size in categorizing images in classes, but it is right to know that by using a significant part of the ear such as the Helix and having the images captured at the same distance, one could argue that the size of the image might be useful in making such conclusive assumption in grouping the images. Our conceptual connotation of the dimensionality of the Helix is the area of the rectangle made by the landmark points Lp1 and Lp2 and the distance between Sp and Wp as shown in figure 10, since the Helix sparse from Sp, Lp1, and Wp. The reason for using this shape dimension is due to the direct relationship between the Helix distance (Sp to Wp) and orthogonal Landmark (Lp1 and Lp2), this distance is calculated using Euclidean distance measurement.

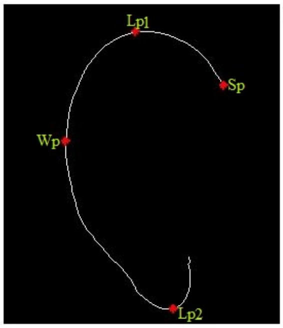


Figure 10: Keypoint Detection

Euclidean Distance

Euclidean distance is the distance between two points in Euclidean space, which involves the computation of two dimensional spaces. Giving two points Wp and Sp with coodinates $(\mathrm{Wp1}, \mathrm{Wp2})$ and $(\mathrm{Sp1}, \mathrm{Sp2})$ respectively, the euclidean distance $\mathrm{d}(\mathrm{Wp}, \mathrm{Sp})$ is given as:

$$\mathrm{d}(\mathrm{Wp}, \mathrm{Sp}) = \sqrt{(\mathrm{Wp1} - \mathrm{Sp1})^2 + (\mathrm{Wp2} - \mathrm{Sp2})^2}$$

In the same vain, considering points $\mathrm{Lp1}$ and $\mathrm{Lp2}$ with coordinates $(\mathrm{Lp11}, \mathrm{Lp12})$ and $(\mathrm{Lp21}, \mathrm{Lp22})$ respectively, the Euclidean distance $\mathrm{d}(\mathrm{Lp1}, \mathrm{Lp2})$ is given as:

$$\mathrm{d}(\mathrm{Lp1}, \mathrm{Lp2}) = \sqrt{(\mathrm{Lp11} - \mathrm{Lp21})^2 + (\mathrm{Lp12} - \mathrm{Lp22})^2}$$

So the dimensionality of the helix will be given as:

$$\mathrm{d}(\mathrm{H}) = \mathrm{d}(\mathrm{Wp}, \mathrm{Sp}) * \mathrm{d}(\mathrm{Lp1}, \mathrm{Lp2})$$

Sum of Squared Differences

Sum of Squared Differences (SSD) is one of simplest correlation based measures that is used to either classify or match the similarities of patterns. This measure takes a perceived dimensionality values to compare its resemblance with a test data (vector) which have an inverse relationship with the distance. One of the advantages of this measure is its simple and flexible computational capabilities. The SSD takes the difference of the estimator and dependant variables (vectors of true values), and then squares the sum of their differences. This can be defined as in the formula:

$$d(a,b) = \sum_{u,v} (f(u,v) - m(u-a, v-b))^2$$

Given that f is the image and p is the matching image, while u and v are positions over the matching image at a and b respectively.

The Sum of Squared difference classifier applied in this paper designed three estimators using the Maximum, Minimum, and the mean of the two values of the feature vectors extracted from the Helix to form three classes which are namely: big, small and medium ear respectively. Having designed the classes, the images are grouped according to classes by iteratively computing the differences between each class values and the true value. The result is then squared and the feature vector is then classified using minimum distance concept, which search for the shortest distance from the resultant outputs.

$$D = \mathrm{Min} \sum_{i \in x, n \in y} (x_i - y)^2$$

Where:

D is the minimum class difference among the three classes under consideration

x and y are the classes and the true value (feature vectors) of the pattern. While i shows the number of classes involved.

Table 1: Classification Result with Lobule Chain Code Signature

Image No	Feature Vectors	Class type	Image No	Feature Vectors	Class type
11	444344435544344	Lobed	13	766666666666665	Lobed
21	566666666667666	Lobed	23	666665666566566	Lobed
31	666666666666566	Lobed	33	666766666666666	Lobed
41	077707777767766	Lobeless	43	707077077707676	Lobeless
51	667666676666666	Lobed	53	767667666766766	Lobed
61	766666766666666	Lobed	63	667667666676666	Lobed
71	666666675665565	Lobed	73	777077777677677	Lobeless*
81	767777777677777	Lobeless	83	777677777777707	Lobeless
91	776767676676666	Lobed	93	665555554544454	Lobed
101	666666665665655	Lobed	103	666666656655656	Lobed

Table 2: Classification Result with Helix Dimensionality vector

Image No	Feature Vectors	Class(1,2,3)	Class type	Image No	Feature Vectors	Class(1,2,3)	Class type
11	40261	1. 280194121 2. 22458121 3. 52722121	2	13	40411	1. 275194921 2. 21058921 3. 54922921	2
21	47075	1. 98505625 2. 4305625 3.198105625	2	23	46494	1. 110376036 2. 2232036 3. 182088036	2
31	33384	1. 557715456 2. 134931456 3. 147456	3	33	31382	1. 656281924 2. 185449924 3. 2617924	3
41	50445	1. 42968025 2. 29648025 3. 304328025	2	43	51680	1. 28302400 2. 44622400 3. 348942400	1*
51	56940	1. 3600 2. 142563600 3. 573123600	1	53	57825	1. 680625 2. 164480625 3. 616280625	1
61	35728	1. 452497984 2. 85969984 3. 7441984	3	63	36806	1. 407797636 2. 67141636 3. 14485636	3
71	43274	1. 188403076 2. 2979076 3. 105555076	2	73	49068	1. 62916624 2. 16548624 3. 258180624	2
81	41385	1. 243828225 2. 13068225 3. 70308225	2	83	40584	1. 269485056 2. 19501056 3. 57517056	2
91	45675	1. 128255625 2. 455625 3. 160655625	2	93	47060	1. 98803600 2. 4243600 3. 197683600	2
101	43416	1. 243828225 2. 13068225 3. 70308225	2	103	38570	1. 339664900 2. 41344900 3. 31024900	3*

Experiment and Results

For the experimental validation of the proposed classification scheme, the University of Science and Technology, Beijing (USTB) ear database II was used. As earlier discussed, it contains 304 images from 77 candidates with 4 images from each candidate, captured under illumination and angles. But 2 images each from the 77 candidates were used making it a total of 154 images since the scheme is an orientation based. The Chain Code signature of these two sets of images is built as discussed previously, by extracting the Chain Code feature vectors from the ear edge image detected. Given that the average number of Chain Code signature for each image is from 400 to 450 codes, it is useful to then concentrate our attention on the Chain Code signature of the Lobule. Thus with this, two sets of Chain Code Signature of the Lobule was built thereby resulting to having a testing and training data respectively. The set from a posture captured from a normal environment is used as a training data and the other as a testing data, though the two can be used interchangeably. Hypothetically, two different classes where modelled based on the shape of the Lobule which translates to the chain code signature. During the training, the Chain Code Signature of the image are grouped and stored based on the orientation of the codes and subsequently, the testing data is used on the classifier to validate its accuracy. It is observed that, since the two sets of images where captured under different angles, the orientation of the Chain Code Signature differed but not much because most of the images were properly classified based on the proposed scheme. Meanwhile, those that were wrongly classified was classified based on the ugly shape of the pinna, as this increases the deviation angle among the two sets of data thereby increasing their chain code orientation. Similarly, all the Chain Code Signature of the sets is now used as a test data for the classification purposes and it was also observed that all the first sets of data were accurately classified, while the second set was not when it is compared with class member of each pair of feature vector from same candidate, taking note on the type marked with asterisks in Table 2.

Conceptually, three classes of ear were built using the Helix dimensionality features which is extracted from the region as discussed in the previous section. Been that the feature vector is a dimensionality measure; the sum of square difference classifier ensures a satisfactory group result of some of the results as shown in table 3. It should be that the test data will have to belong to one of the three classes and will certainly not belong to any other class. The variation in the class differences as shown in the asterisked class type column in the tables can be attributed to the illumination, hair occlusion, and angle of acquisition of the image. Therefore, this affected the second classification scheme more, since the angle of acquisition created a major deviation on the feature of the vectors.

$$\text{Percentage accuracy of the scheme} = \frac{\text{number of correct grouping}}{\text{Total number of samples}} * 100$$

The empirical evaluation of the results shows that the classification scheme that utilizes the lobule structure performed better than that of the Helix structure as shown in table 4 below. The reasons is as a result of translation problem, as the angle of orientation varies and so do the spatial information of the image and this also influences the helix dimensionality feature of the vectors.

Table 3: Experimental Result

S/No	Classification Scheme Feature	Percentage Accuracy (%)
1	Lobule	94.80
2	Helix	92.20

Conclusion

This paper proposed a human ear classification scheme using Chain Code Signature and Dimensionality features of the Lobule and the Helix respectively. USTB ear database was used for the evaluation of the experimental result of the classification method, with a success rate of 94.8% and 92.2%. Due to the poor quality of some the images which our pre-processing activities were not able to cater for, some of the ear images were erroneously classified. On comparing the two basic features that were used, the Lobule Chain Code Signature gave a more accurate listing of the classes on the same samples of images. This is witnessed in the cases where the second feature vectors failed on a noisy edge which is used for classification purpose and this experimental result demonstrates the power of using prominent parts of the ear for its classification. Therefore, the use of the Tragus part of the ear for classification is on-going to explore its classification prowess using a basic chain code signature.

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