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Factor Analysis Assisted Classification of Ear Images Based on GLCM Features.

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Abstract

It is well known fact the Gray Level co-occurrence matrix (GLCM) is immensely used to extract second order statistical textual features of an image. These features have been variously used by researchers. In this paper, GLCM features of 800 right ear images have been used. The case in point is ear biometrics; the 22 features extracted from the images were subjected to factor analysis for delineating the most predominant textural attributes and the factors involved with them. The result shows that three factors qualified by Kaiser's criterion were used to develop a person identification system, which showed 97% of recognition accuracy.

Keywords: Ear Images, Biometrics, GLCM features, Factor analysis, Person identification system.

1. INTRODUCTION

Texture analysis of an image has been a long standing method aimed at representing underlying characteristics of texture of an image so that it could be used for accurate classification and segmentation of objects. It is exactly here that gray level co-occurrence matrix (GLCM) comes into play. Among several GLCM based features, traditional only four important features namely, angular second moment, correlation, inverse difference moment and entropy are computed. These four measures use for image classification task [1].Texture is one of the important characteristics used in identifying objects or regions of interest in an image. Texture contains important information about the structural arrangement of surfaces. The textural features based on gray-tone spatial dependencies have a general applicability in image classification. The three fundamental pattern elements used in human interpretation of images are spectral, textural and contextual features. Spectral features describe the average tonal variations in various bands of the visible and/or infrared portion of an electromagnetic spectrum. Textural features contain information about the spatial distribution of tonal variations within a band. The fourteen textural features proposed by Haralick et all [7] contain information about image texture characteristics such as homogeneity, gray-tone linear dependencies, contrast, number and nature of boundaries present and the complexity of the image. Contextual features contain information derived from blocks of pictorial data surrounding the area being analyzed.

Haralick et. all first introduced the use of co-occurrence probabilities using GLCM for extracting various texture features. GLCM is also called as Gray level Dependency Matrix. It may be connoted as a two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship.

Following predominant GLCM features are briefed for the sake of completeness.

1. Angular Second Moment: Angular Second Moment is also known as Uniformity or Energy. It is the sum of squares of entries in the GLCM Angular Second Moment measures the image homogeneity. Angular Second Moment is high when image has very good homogeneity or when pixels are very similar. The range will be [0, 1] and the energy will be 1 for constant image.
2. Entropy: This statistic measures the disorder or complexity of an image. The entropy is large when the image is not texturally uniform and many GLCM elements have very small values. Complex textures tend to have high entropy. Entropy is strongly, but inversely correlated to energy.
3. Sum of Absolute Difference: Sum of Absolute Difference is a widely used and extremely simple algorithm for finding the correlation between image blocks. It works by taking the absolute difference between each pixel in the original block and the corresponding pixel in the block being used for comparison.
4. Inverse Difference Moment: Inverse Difference Moment (IDM) is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high.
5. Correlation: Correlation measures the linear dependency of grey levels of neighboring pixels. Digital Image Correlation is an optical method that employs tracking & image registration techniques for accurate 2D and 3D measurements of changes in images. The correlation is 1 or -1 for perfect positively or negatively, and it is NaN for constant image.
6. Contrast: It measures the intensity contrast between a pixel and its neighbor over the whole image. Contrast

will be zero for the constant image; it is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies.

Section 2 explains the details of factor analysis. Section 3 explains the details application of analysis in various allied fields including image processing. Section 4 explains the data collection, the preprocessing and related work that is followed by presentation of the methodology used in section 5. Section 6 makes a discussion on results and finally the paper concludes in section 7.

2. FACTOR ANALYSIS

Factor analysis is a collection of methods used to examine how underlying constructs influence the responses on a number of measured variables. Factor analyses are performed by examining the pattern of correlations (or covariance) between the observed measures. Measures that are highly correlated (either positively or negatively) are likely influenced by the same factors, while those that are relatively uncorrelated are likely influenced by different factors.

There are seven basic steps to performing an Exploratory Factor Analysis (EFA) [10]:

1. Collect measurements. We need to see that the variables are on the same (or matched) experimental units.
2. Obtain the correlation matrix. Second we need to obtain the correlations (or covariances) between each of the variables.
3. Select the number of factors for inclusion. Sometimes you have a specific hypothesis that will determine the number factors you will include, while other times you simply want your final model to account for as much of the covariance in your data with as few factors as possible. If you have k measures, then you can at most extract k factors. There are a number of methods to determine the “optimal" number of factors by examining your data. The Kaiser criterion states that you should use a number of factors equal to the number of the Eigen values of the correlation matrix that are greater than one. The “Screen test” states that you should plot the Eigen values of the correlation matrix in descending order, and then use a number of factors equal to the number of Eigen values that occur prior to the last major drop in eigen value magnitude.
4. Extract your initial set of factors. You must submit your correlations or covariances into a computer program to extract your factors. This step is too complex to reasonably be done by hand. There are a number of different extraction methods, including maximum likelihood, principal component, and principal axis extraction. The best method is generally maximum likelihood extraction, unless you seriously lack multivariate normality in your measures.
5. Rotate your factors to a final solution. For any given set of correlations and number of factors there are actually an infinite number of ways that you can define your factors and still account for the same amount of covariance in your measures. Some of these definitions, however, are easier to interpret theoretically than others. By rotating your factors you attempt to find a factor solution that is equal to that obtained in the initial extraction but which has the simplest interpretation. There are many different types of rotation, but they all try make your factors each highly responsive to a small subset of your items (as opposed to being moderately responsive to a broad set). There are two major categories of rotations, orthogonal rotations, which produce uncorrelated factors, and oblique rotations, which produce correlated factors. The best orthogonal rotation is widely believed to be Varimax. Oblique rotations are less distinguishable, with the three most commonly used being Direct Quartimin, Promax, and Harris-Kaiser Orthoblique.
6. Interpret your factor structure. Each of your measures will be linearly related to each of your factors. The strength of this relationship is contained in the respective factor loading, produced by your rotation. This loading can be interpreted as a standardized regression coefficient, regressing the factor on the measures. You define a factor by considering the possible theoretical constructs that could be responsible for the observed pattern of positive and negative loadings. To ease interpretation you have the option of multiplying all of the loadings for a given factor by -1. This essentially reverses the scale of the factor, allowing you, for example, to turn an “unfriendliness” factor into a “friendliness” factor.
7. Construct factor scores for further analysis. If you wish to perform additional analyses using the factors as variables you will need to construct factor scores. The score for a given factor is a linear combination of all of the measures, weighted by the corresponding factor loading. Sometimes factor scores are idealized, assigning a value of 1 to strongly positive loadings, a value of -1 to strongly negative loadings, and a value of 0 to intermediate loadings. These factor scores can then be used in analyses just like any other variable, although

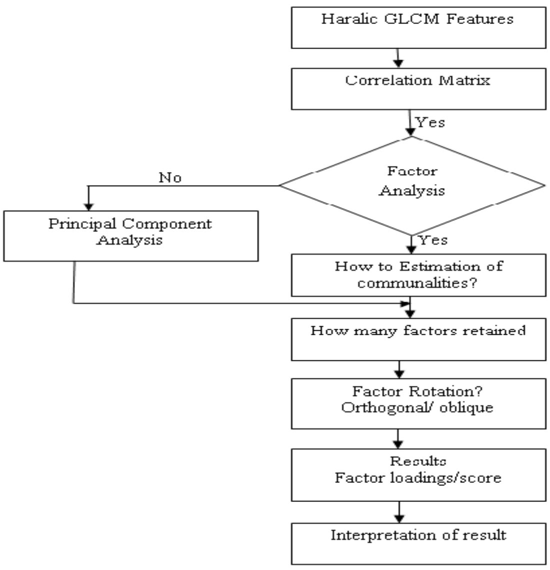

Figure 1: Flow chart of steps in Exploratory Factor Analysis.

The above elaborated steps of factor analysis are portrayed through a flow diagram in figure 1.

3 Literature Survey

Texture Analysis of SAR Sea Ice Imagery: Author's have used the following methods and uses GLCM to quantitatively evaluate textural parameters and determine which parameter values are best for mapping sea ice textures. The importance of gray-level quantization, displacement and orientation factors for representing sea ice in synthetic aperture radar (SAR) imagery is studied [11]. The following three types of co-occurrence matrices were studied as follows: Mean Displacement Mean Orientation, Optimal Displacement Mean Orientation and Optimal Displacement Optimal Orientation.

Synthesis of Textures: The analysis uses the algorithm to generating synthetic textures based on GLCM is presented, [12] which are used to imitate real textures taken from satellite images. A histogram is computed from the desired GLCM. Then an initial image that has the desired histogram is randomly generated. Further, a chain of images is iteratively produced such that the new image is improvement over the initial in terms of error of distance of current co-occurrences from desired co-occurrences. The iteration stops when the error goes below a pre-specified threshold value. The algorithm converges only if a solution exists. The difference between the real and synthetic textures is indistinguishable by the human eye, which implies that co-occurrence features are well suited for characterizing these types of images.

Texture Defect Detection: The method uses the combination of wavelet theory and co-occurrence matrices [13] is used to detect defects in textile images. Texture defect detection can be defined as the process of determining the location and/or extent of collection of pixels in a textured image with remarkable deviation in their intensity values or spatial arrangement with respect to the background texture.

Circular GLCM: The circular GLCM used to study the short wavelength anomalies in the Earth's gravitational field [14]. In this model, the GLCM textural measures use a vector that connects pairs of pixels within a kernel that is moved over the image. This is a unique method as it deals with circular features to enhance the elusive details. The vectors connect points that lie on the perimeter of circles of different radii. A mid-point algorithm is used to select the points that lay on each circle.

Object Recognition and Matching: The application is elaborates a novel method based on quantitative estimation of relations between some elementary image structures, which are represented by elements of special multidimensional co-occurrence matrices (MDCM) [15]. An image of any object can be considered as a composition of elementary structures, the elements of which carry some attributes (e.g. gray level value, gradient magnitude, orientation) and have some relations (e.g. gray level difference, relative gradient orientation). A multidimensional co-occurrence matrix is used where each of the attributes and relations correspond to different axis of the matrix. Object is made recognizable due to the balanced presence of some specific elementary structures present in it.

Image Segmentation and Edge Detection: The concept uses the field of image analysis research for several years. It involves the process of extracting information from an image and analyzing it to achieve a specific goal.

The two main steps involved are:

- Image segmentation: segmentation of an image into homogeneous regions with respect to certain image characteristic.
- Edge detection: the extraction of the locations in the image having changes in intensity.

Color texture classification by integrative co-occurrence matrices: Color is an important issue in digital image processing. It is a vectorial feature assigned to each pixel. Color information improves the results of gray scale texture features.

Two categories of co-occurrence matrices (CMs) are proposed for color texture classification [16]:

- Single channel co-occurrence matrices (SCMs): They consist of gray scale CMs successively applied to separated color channels.
- Multi channel co-occurrence matrices (MCMs): These capture correlation between textures of different color channels.

They provide the opportunity to study the effect of texture and pure color analysis in one unified framework. No spatial adjacency but channel adjacency is regarded.

4 Data for the Model

The ear images used in this work were acquired from students of the Siddaganga group of institutes. The subjects involved were mostly students and faculty numbering around 800. In each acquisition session, the subject sat approximately 1 m away, with the side of the face in front of the camera in an outdoor environment without flash. The images were obtained simultaneously. Care was taken to provide the same illumination conditions for all the captures. All images were enrolled in the gallery of a database. A cross section of the sample database is presented in Figure 2.

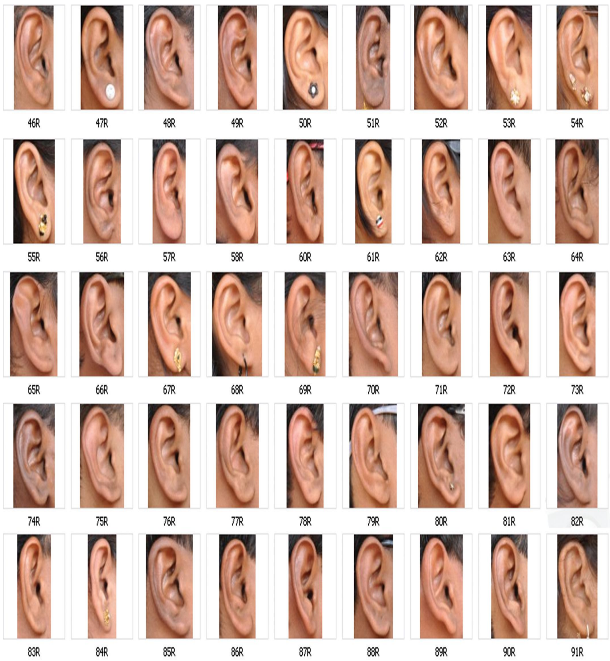

Figure 2: A gallery Sample Database.

The images so obtained were resized in such a way that only the ear portion covers the entire frame having a pixel matrix. The color images were converted into gray-scale images followed by the uniform distribution of brightness through a histogram equalization technique. The delineation of the outer edge of each ear was obtained using a canny edge detection algorithm. The conceptual presentation of the process involved in obtaining GLCM features is shown in Figure 3.

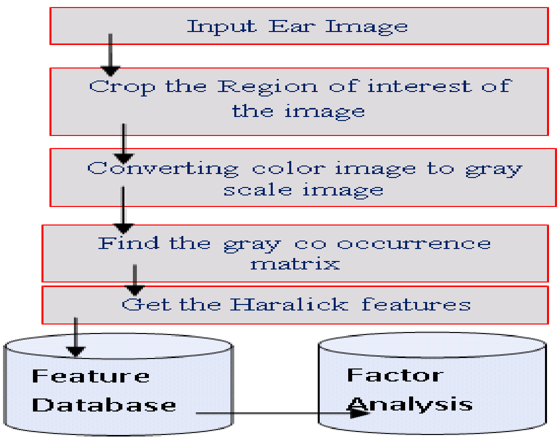

Figure 3: The steps involved in Extracting GLCM Features.

5 The Methodology

The methodology involved in this work includes two steps:

i. Identify the optimum number of classes with minimum overlapping using KNN.

ii. Apply factor method for the extracted features and

iii. Apply BPNN to fine tune the so obtained classes by using optimized number of features obtained in step ii.

A schematic block diagram depicting the methodology is shown in block diagram

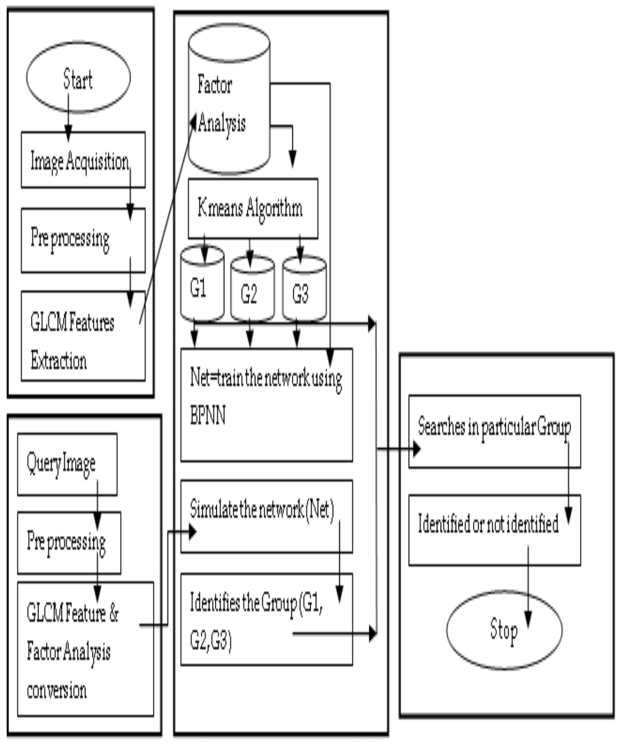

Figure 4 Block Diagram.

A.K-means algorithm

K-means clustering is an iterative, data-partitioning algorithm that assigns *n* observations to exactly one of *k* clusters defined by centroids, where *k* is chosen before the algorithm starts. The purpose of applying the k-means clustering algorithm is to find a set of clustered centers and a partition of training data into subclasses. Normally, the center of each cluster is initialized to a randomly chosen input datum. Then each training datum is assigned to the cluster that is nearest to itself. After training data have been assigned to a new cluster unit, the new center of a cluster *represents* the average of the training data associated with that cluster unit. After all the new clusters have been calculated, the process is repeated until it converges [4]. Series of computational experiments were conducted in order to find optimum number of classes with minimum overlapping. The experiments started with five, four and *three* classes. In all the cases the percentage of overlapping among the classes were verified. It was found that three groups were ideal because of minimum overlapping.

B. Factor Analysis for the features extracted

Factor analysis attempts to identify underlying variables, or factors, that explain the pattern of correlations within a set of observed variables. Factor analysis is often used in data reduction to identify a small number of factors that explain most of the variance that is observed in a much larger number of manifest variables. Factor analysis can also be used to generate hypotheses regarding causal mechanisms or to screen variables for subsequent analysis (for example, to identify collinearity prior to performing a linear regression analysis). It can be done by seeking underlying unobservable (latent) variables that are reflected in the observed variables (manifest variables). There are different methods that can be used to do a factor analysis (such as principal axis factor, maximum likelihood, generalized least squares, unweighted least squares), There are also many different types of rotations that can be done after the initial extraction of factors, including orthogonal rotations, such as varimax and equimax, which impose the restriction that the factors cannot be correlated, and oblique rotations, such as promax, which allow the factors to be correlated with one another. You also need to determine the number of factors that you want to extract. Given the number of factor analytic techniques and options, it is not surprising that different analysts could reach very different results analyzing the same data set. However, we are looking for simple structure. Simple structure is pattern of results such that each variable loads highly onto one and only one factor. Factor analysis is a technique that done on a large sample size. Factor analysis is based on the correlation matrix of the variables involved, and correlations usually need a large sample size before they stabilize.

C. Application of ANN

As a sequel to the first step we grouped the entire database is suitable into three groups, and the next step we use the ANN to train the network with the input and when finally the network is ready, we used the data from the database and then the features extracted of the ear and then it is simulated with the network and we get the particular group the ear identified, then we check in the particular group and display the person identified, the retrieval time based on group and linear search is represented in the Table 7.

6 RESULTS

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. Table 1 represents the values of the gray level co occurrence matrix for a sample of image from the database.

Table 1: Gray level co-occurrence matrix of sample.

	1	2	3	4	5	6	7	8
1	4430	186	0	0	0	0	0	0
2	186	49186	1127	0	0	0	0	0
3	0	1127	94630	1220	0	0	0	0
4	0	0	1220	82566	1309	0	0	0
5	0	0	0	1309	52180	1011	0	0
6	0	0	0	0	1011	60444	584	0
7	0	0	0	0	0	584	22940	214
8	0	0	0	0	0	0	214	6622

The following is the elaborate of factor method, whose outcomes are presented in Table 2:

a. Factor - The initial number of factors is the same as the number of variables used in the factor analysis. However, not all 22 factors will be retained.

b. Initial Eigen values - Eigen values are the variances of the factors. Because we conducted our factor analysis on the correlation matrix, the variables are standardized, which means that the each variable has a variance of 1, and the total variance is equal to the number of variables used in the analysis, in this case, 22.

c. Total - This column contains the Eigen values. The first factor will always account for the most variance (and hence have the highest Eigen value), and the next factor will account for as much of the left over variance as it can, and so on. Hence, each successive factor will account for less and less variance.

d. Percentage of Variance - This column contains the percent of total variance accounted for by each factor.

e. Cumulative Percentage - This column contains the cumulative percentage of variance accounted for by the current and all preceding factors. For example, the third row shows a value of 94.190 this means that the first three factors together account for 94.190% of the total variance.

f. Extraction Sums of Squared Loadings - The number of rows in this panel of the table correspond to the number of factors retained. In this example, we requested that three factors be retained, so there are three rows, one for each retained factor. The values in this panel of the table are calculated in the same way as the values in the left panel, except that here the values are based on the common variance. The values in this panel of the table will always be lower than the values in the left panel of the table, because they are based on the common variance, which is always smaller than the total variance.

g. Rotation Sums of Squared Loadings - The values in this panel of the table represent the distribution of the variance after the varimax rotation. Varimax rotation tries to maximize the variance of each of the factors, so the total amount of variance accounted for is redistributed over the three extracted factors.

TABLE 2: VARIANCES OF THE ATTRIBUTES

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.462	56.647	56.647	12.462	56.647	56.647	11.388	51.765	51.765
2	5.835	26.524	83.171	5.835	26.524	83.171	4.676	21.256	73.020
3	2.424	11.019	94.190	2.424	11.019	94.190	4.657	21.169	94.190
4	.752	3.418	97.608						
5	.207	.940	98.548						
6	.162	.736	99.284						
7	.077	.351	99.635						
8	.040	.183	99.818						
9	.024	.109	99.927						
10	.006	.029	99.956						
11	.005	.024	99.980						
12	.004	.017	99.997						
13	.000	.002	99.999						
14	.000	.001	100.000						
15	1.924E-005	8.747E-005	100.000						
16	7.536E-007	3.426E-006	100.000						
17	5.556E-009	2.525E-008	100.000						
18	5.125E-012	2.329E-011	100.000						
19	2.618E-015	1.190E-014	100.000						
20	2.119E-015	9.633E-015	100.000						
21	-1.721E-030	-7.823E-030	100.000						
22	-1.420E-018	-6.456E-018	100.000						

Table 3 represents the communalities before and after execution the principal component analysis. This works on the initial assumption that all the variance are common, therefore before execution the communalities are all 1. The communalities in the column labeled as extraction reflect the common variance in the data structure. So, for example it can be said that 97.3 %of the variance associated with the attribute 1 is common or shared or variance.

Table 3: Communalities

	Initial	Extraction
autoc	1.000	.973
contr	1.000	.991
corrm	1.000	.954
corrp	1.000	.954
cprom	1.000	.613
cshad	1.000	.772
dissi	1.000	.996
energ	1.000	.946
entro	1.000	.989
homom	1.000	.995
homop	1.000	.995
maxpr	1.000	.782
sosvh	1.000	.973
savgh	1.000	.977
svarh	1.000	.956
senth	1.000	.984
dvarh	1.000	.991
denth	1.000	.990
inf1h	1.000	.991
inf2h	1.000	.913
indnc	1.000	.996
idmnc	1.000	.992

Table 4 Component Matrix[a]

	Component		
	1	2	3
autoc	.493	.740	-.429
contr	.967	-.177	.119
corrm	-.877	.409	.150
corrp	-.877	.409	.150
cprom	-.243	.562	.519
cshad	-.232	-.353	.738
dissi	.978	-.169	.096
energ	-.498	-.714	-.427
entro	.743	.528	.398
homom	-.978	.165	-.088
homop	-.978	.166	-.090
maxpr	-.339	-.694	-.407
sosvh	.499	.737	-.427
savgh	.549	.673	-.467
svarh	.425	.719	-.513
senth	.579	.678	.431
dvarh	.967	-.177	.119
denth	.977	-.152	.085
inf1h	.952	-.277	-.024
inf2h	-.653	.660	.305
indnc	-.979	.168	-.093
idmnc	-.970	.176	-.116

Table 4 presents the matrix loadings called the component matrix for the method. It loads those factors, which are very near to 1.

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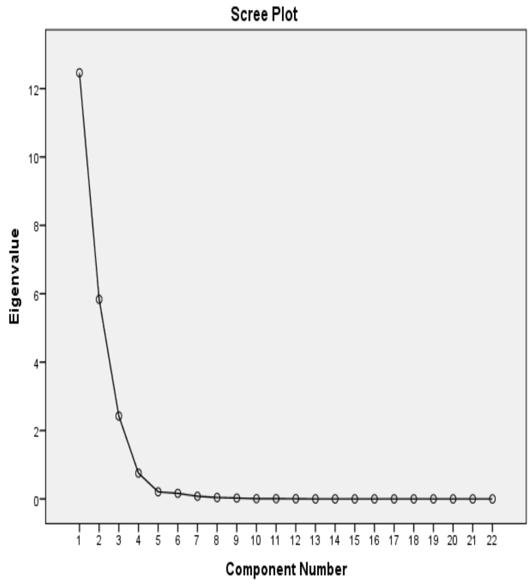

Figure 5: Eigen values verse the number of features

Figure 5 shows the Eigen value verses number of component, it shows that how many attributes can be considered using the Kaisers criterion, it can be represented. Kaiser's criterion gives recommendations for the smaller sample size greater than 250. The average of the communalities can be found by adding them up and dividing by the number of communalities.

KE= (20.721/22)=0.94186.

The screen plot is shown in Figure 5, the curve is difficult to interpret because the curve begins to tail after three factors, but there is another drop after factor four because a stable plateau is reached.

Factor rotation alters the pattern of the factor loadings, and hence can improve interpretation. Rotation can best be explained by imagining factors as axes in a graph, on which the original variables load. There are several methods to carry out rotations, namely varimax, quartimax, equamax, direct oblimin and promax. The first three options are orthogonal rotation; the last two oblique. It depends on the situation, but mostly varimax is used in orthogonal rotation and direct oblimin in oblique rotation. Orthogonal rotation results in a rotated component / factor matrix that presents the 'post-rotation' loadings of the original variables on the extracted factors, and a transformation matrix that gives information about the angle of rotation. In oblique rotation the results are a pattern matrix, structure matrix, and a component correlation matrix. The component correlation matrix presents the correlation between the extracted factors / components, and is thus important for choosing between orthogonal and oblique rotation. Consider the Table 4 and Table 5 with the unrotated solution. Before rotation, most variables loaded highly on the first factor and the remaining factor.

Table 5. Rotated Component Matrix

	Component		
	1	2	3
autoc	-.145	.918	.332
contr	-.966	.097	.197
corrm	.957	-.121	.168
corrp	.957	-.121	.168
cprom	.411	-.102	.682
cshad	.037	-.823	.209
dissi	-.972	.122	.189
energ	.207	-.283	-.904
entro	-.503	.263	.816
homom	.970	-.130	-.186
homop	.970	-.127	-.187
maxpr	.068	-.237	-.838
sosvh	-.152	.917	.333
savgh	-.221	.921	.274
svarh	-.087	.945	.244
senth	-.297	.282	.902
dvarh	-.966	.097	.197
denth	-.963	.139	.193
inf1h	-.983	.134	.027
inf2h	.839	-.009	.502
indnc	.971	-.124	-.188
idmnc	.968	-.100	-.196

Table 6 Component Transformation Matrix

Component	1	2	3
1	-.920	.202	.335
2	.369	.735	.569
3	.131	-.647	.751

Table7 represents the time taken to retrieve the image after feature extraction and verifying in the database based on the linear searching or by using artificial neural network trained with the dataset and the time taken to retrieve the matched the image.

Table 7: Retrieval time for identification of person ear.

Sl.no	Image no	CPU time for Linear search Milliseconds	CPU Time for Group Search Milliseconds
1.	1	0.016	0.035
2.	60	0.024	0.024
3.	110	0.025	0.025
4.	151	0.023	0.022
5.	281	0.031	0.025
6.	603	0.070	0.012
7.	584	0.069	0.014
8.	534	0.068	0.019
9.	462	0.064	0.022
10.	456	0.059	0.022

7 CONCLUSION

This paper presented a texture based image classification guided through factor analysis with a special reference to ear biometrics. This work showed GLCM features like entropy, inverse difference moment, angular second moment and co-relation are the deciding factors or GLCM features. This work also emphasized the fact that texture based features of an Ear images could also be used for classification and concurrent person identification in biometric system.

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