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FINGERNAIL BIOMETRIC FOR EFFICIENT PERSON IDENTIFICATION

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***Abstract*— We propose fingernails as novel biometric for person recognition and classification. The recognition method includes multiple steps. Preprocessing of biometric images to improve and select foreground finger information by eliminating noisy background with smooth histogram thresholding. Exercise automatic separation of unchanging nail plate structure from changing distal free nail, through local contrast enhancement that organizes fingernail regions patterns for segmentation by watershed method, which is exercised based on maxima and minima properties of marker controlled principles to get appropriate fingernail parts. Also select intended nail plate region as ground truth. Nail plate datasets from both methods show improved and encouraging similarity results. Feature extraction includes nail plates shape attributes (filled area, weighted centroid), context based information (nail plate boundary, ellipse fit) and contour measures (perimeter, eccentricity). Additionally, covariance along major and minor axes using singular value decomposition is calculated for roundness, as dimensionless measure. Classification of automatically selected nail plate dataset features is experimentally evaluated. Proposed algorithm selects collection of features samples of different orientations for training and testing using k-NN classifier. Confusion matrix is constructed to indicate types of classification errors and to evaluate overall accuracy. The classification results are hopeful with overall recognition rate of 87.5% for combination of training and test samples. Initial fingernail plate recognition is promising, supporting its use for biometric application.**

Keywords—**Finger shape, histogram thresholding, fingernail plate, Contrast-Limited Adaptive Histogram Equalization (CLAHE), watershed segmentation, geometric properties, Singular Valued Decomposition (SVD), k-Nearest Neighbor (k-NN).**

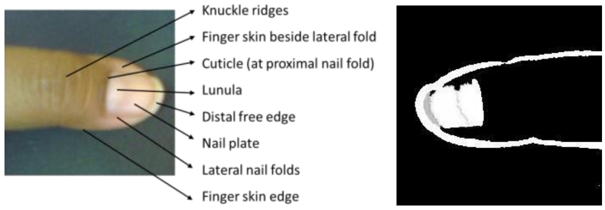
I. INTRODUCTION

As humans we recognize each other conveniently with some acquired familiarity (information). Whereas institutions collect and store information about people who are part of their system either to identify, validate, or provide related services whenever necessary. A biometric is considered in fact as unique and difficult information to impersonate. Still, single biometric features are signaling as insufficient checks, not able to address today's biological or socio-physical complexities. With increasing population and associated fraudulent incidents, complex information storage methods have become necessary in many areas of automatic systems. The conventional passwords are also prone to spoofing problems (knowledge based can be stolen or forgotten) and have become difficult to establish concrete identity of individuals with high population density. Secondly, pin numbers, too many passwords, bar coding in many transaction cards, access digits and other numbers all have somewhat common information amongst people. Many people use one-to-many strong passwords (quite confusing) for all transactions and can be quite dangerous if it falls in the hands of wrong people. Hackers have found ways to trick the existing types of data and are gaining familiarity to the information of protected places or safeguarded premises. It is easy for them to steal or guess keys to ones identity after reading some clues or by generating some combination of secret codes and to get charge to all the secured data. The limitation of knowledge based system and hacker tricks has led to reasonable amount of biometric experiments to solve existing recognition problems. Experts in related areas are challenged to find ways around more advanced, better secured, not so easy admittance or identity.

A person automatically carries along multiple biological/biometric traits as additional information that cannot be easily let go or forgotten. Since few years, many software and web-technology service companies have shown interest to use biometric to authentication, protect their network-based information available to users through mobiles, computers and other communication means. The networks' technology is real, resourceful, and cannot be made confidential in the private sector's usage. We are already familiar with the usage of some of the physical traits via biometric authentication systems, such as face, iris, and fingerprints. The other personal characters, particularly sparsely measured includes ear, palm print, hand veins, voice [13] etc. To possibly consider the above mentioned requirements, we in this work, suggest an encouraging fingernail biometric that is new, approachable and easy of consent. Person hands and fingers are considered as one of the primary tools for interacting with physical objects that the individual wishes to. One of the current applications of fingers is to exercise display screens to enhance interactions with touch screen sensors. Theoretically, there are many advantages of it in day to day functioning. But we do not have fingernail based automated application systems addressing different problems. The fingernail shape can thus be coded easily for feature extraction to identify persons in relevant fields of interest, alongside existing biometrics and soft biometrics [26].

In the recent past, interestingly human fingernails are discussed both in theory and survey intended for computer vision measures. Additional applications are found in literatures based on robotics, some implementations in Artificial Intelligence (AI), few works are recently found in pattern recognition, digital image processing and so on. Referred examples are; a) Karbhari V. Kale, et al., adopt multiple modality for biometric system using fingernail and finger knuckle [22], b) Igor Barros Barbosa et al., talks about possible transient biometric attributes using fingernails, [23], c) Amioy Kumar et al., have proved use of finger nail plates in biometric authentication [24], d) Kavita Jaba Malar, et al., have explored fuzzy measures for fingernail matching [25]. Thus, fingernail applications are not absolutely made use of and their advantages are not yet focused. Gradually, the fingernails recognition as a biometric is gaining support and acceptance in significant circumstances like segmentation, classification or identification in digital system.

Fingernails have interesting characteristic with small structural variation over a person's life period. Skin and fingernail regions display many variations amongst individuals and also differ between fingers of identical twins. There are shape and size differences between fingers of same individual and is comparable to finger print patterns with performances. In the visible band, fingers exhibit freckles, of illumination variations, or bright spots [21]. Fingernail structure with features required for our experimentation is labelled as in Fig. 1(a), output achieved is in Fig. 1. (b). The approaches to fingernail selection and its smaller sub objects, if done manually can get affected structurally due to human selection which subconsciously depends on psychological opinion or mental state of mind, rather than physical measure. It loses focus and efficiency when systems are time constrained and responds to large population [17]. If differences in bright, more bright, just bright have to be considered, it becomes very difficult and requires more attention while identifying the nail structure areas into its sub parts. As a result, it affects the system evaluation of fingernail parts recognition.



(a) (b)

Fig. 1. (a) Original color image with labeled parts, (b) Binary image programmatically identified with similar parts as in Fig1(a).

Hence, we present fingernails as new digital patterns and define a method that can get parts almost accurately [1, 2], which in turn helps generate nail plates to recognize and classify person's within biometric systems. In contrast to growing distal free nails, it is the actual nail plate textures that are naturally present without change in shape probably with minor variations in outline. The duration of changes varies from person to person stretching from 3 to 6 months as in Fig. 2. As a result, it is presumed to be helpful in the construction of more acceptable attributes for recognition systems. The general idea of quality measure of segmented results is basically to help in constructing and understanding of the overall performance of the procedure followed.

The purpose of the proposed approach is to identify fingernail parts as correctly as possible in spite of possible inherent errors exhibiting variations in patterns from digitally read finger images. It is clear from earlier outcomes that fingernail is one of the correct means of measures as unique features. It is also one of the novel, easily available, less intrusive, and more difficult to forge biometric finding as it holds in present day requirements. We demonstrate that the images of the fingernails constitute various pattern attributes for a recognition system and an example is shown in Fig. 3(a-c), (expected fingernail features as sub-regions). Fingernail parts are identified by differentiating fingernail plate with lunula included as one distinct part and distal free nail edge as another. Both automatic segmentation region and ground truth selection patterns are experimented for region features calculation and evaluation of the results. With prior knowledge suggesting that fingernail within finger structure contains the brighter regions in every image of nail plate database used for biometric recognition.

(a) (b) (c)

Fig. 2. (a) Nail plate and distal free nail marked, (b) complete fingernail, (c) nail plate separated from distal free nail [27].

The remaining part of the paper is organized as follows: Section II – briefly presents the procedure of in-house finger data collection, pre-processing of finger images, improvement of picture contrast, segmentation of finger skin pattern, and categorize its well-defined parts. The method contains all procedures of marker controlled watershed approach, including noise correction, region marking and feature extraction and evaluation with ground truth (manually identified nail parts). Effort is to arrive at good segmentation results with careful region approximation of complete fingernail pattern detection [12]. Section III – Explains levels of features; to identify automatic nail plate region shape parameters, expand these attributes for improved nail plate adaptation. Features from refined geometric area along with statistical attributes [1, 3] are also measured for evaluation of context based characteristics, SVD measures are calculated for fusion of properties to maintain classification results. Section IV- k-Nearest Neighbors are calculated here to carryout best match through test/train datasets. Enrolled nail plate features are stored information part of person's database in memory. Section V – Quantifies biometric recognition in confusion matrix for person classification. And lastly tabulated discussion of confusion matrix confirms good results, supports expected outcome that is achievable, and puts across few fingernail future perspectives.

II. PROPOSED ALGORITHM

A. Data Collection

We have collected data for the experimentation considering top view of finger images captured with resolution 2.0 MP (960x1280 pixels) using a digital camera, placed 6 inches away from finger position (objective). The total collection is about 200 finger images in the following manner; 20-people, thumb fingers of a person is considered. Five images per finger, with each finger having effortless positional changes, when placed on table top are captured and few examples are shown in Fig. 3. For initial experimentation of biometric classification, only thumb images are selected from the in-house database acquired (fingernail) and tested in this program. That is, 2 thumb fingers * 20 persons * 5 views for every finger is measured for recognition. Design of training and testing a classifier is prepared by 60% and 40% of images respectively. All images of fingers are normalized to size 600x600 pixels in order to remove oversized background, without changing initial resolution. The colour spectrum of image highlights textural patterns [5, 8] of a variety of finger and fingernails, making it more discriminative measurements for recognizing people.

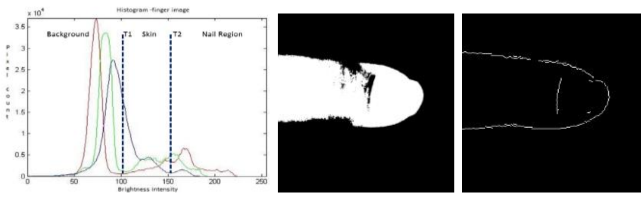
Fig. 3. Finger images collected from in-house setup; examples show variations in fingernails structure and views

B. Finger Shapes

Skin texture; it has heterogeneous description, without very well defined contour formation, due to curved surface that causes shadow and brightness effects [11, 16]. It is not always possible to deal with high resolution image and distinction of all objects to get good boundaries that are smooth and/or without discontinuous edges. There is a necessity to developed step to find nearest adaptive global threshold to the general problem.

Foreground segmentation; is also normal practice not to use original images directly in object boundary findings. Images are developed to improve visual clarity before object analysis (features). In the process of controlled finger edge detection, systematic value for thresholding is established from histogram smoothing so as to ignore smaller and less contrast edges as shown in Fig. 4 (a). The purpose is to segment complete finger spectrum as one largest filled area, having set of pixels within its structure (appropriate border line). This involves background modeling for accurate finger shape detection. Histogram equalization to improve contrast and smooth frequency curve calculation to select proper thresholding measures is as described in Fig. 4(a). Output of region and contour detection process is shown in Fig. 4(b-c).

Edge detection; after boundaries are extracted, filtering out sections of connected pixel areas below a threshold is necessary. The smaller, irregular parts from largest identified objects are effectively removed. Any holes in the finger region caused by reflections or other distortions are filled by looking into sections of blank pixels in the area. Our modified, new approache effectively removes speckles, handels possible noise problems, corrects unsmooth or irregular parts from resultant output for almost accurate finger shape identification. We propose to adopt the inside area of finger boundary represent as single object of foremost interest (i.e., finger ROI). Finger as foregrond object however has facilitated to process the arrangement of fingernail parts in advance steps to consider only the fixed nail plate region for feature analysis. Finger edge finding also maintains shape context features of nail plate in further experimentation.



(a) (b) (c)

Fig. 4. (a) Histogram plot of intensity enhanced finger image, (b) foreground segmentation, (c) finger edge detection.

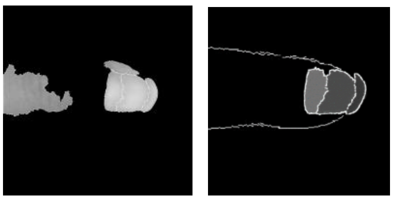
C. Fingernail Parts

Contrast enhancement; variation in image brightness explains the need for image clarity and therefore multispectral digital images are converted into gray scale before enhancing its contrast levels. Contrast improvement of the "desired" regions depends on the appearance of objects in images. In the "desired" system for fingernail region, CLAHE enhances every division iteratively. The method avoids noise amplification in images because local intensity is adjusted [20].

Watershed boundary and local intensity minimum; the enhanced image is binarized by Otsu's method that aims at iterating through all the possible threshold values, calculating spread measure in an optimal manner. Binary image has a possibility of gradients by small variations due to random noise. Unexpected, random blob areas are results of over segmentation by the occurrence of many local minima. To decrease this effect of watershed transformations, the morphological operations are applied to drop few areas and fill regions with small holes in spatially connected boundary areas [9, 10]. Method is invariant to orientation, scaling and translation. Technique inherently focuses to correct many uncertain noises like; redundant or unwanted region areas, edges, truncated contours.

Marker controlled segmentation; the marker controlled watershed helps clearly separates even the homogeneous gray-tones of fingers textures, treating it as topographic surface (markers). The transformation finds "catchment basins" and "watershed ridge lines" in images by marking it as a surface with light pixels as high and dark pixels as low areas , for gradient set of pixel points and is represented by *f* function. Topographic surface *S*, has the highest Gradient Magnitude Intensity (GMI) pixels as region boundaries. Local Intensity Minimum (LIM), pixels are common watershed boundary lines. Pixels with a common minimum appear like segment sink or basins. *M* is a minima in *f* made up of all possible connected components of regions M_i in f [4, 7]. The image intensity minima transform identifies valleys that are deeper than a particular threshold to change a valley's pixel to contain only zeros and given by Eq. 1.

$$\forall s_i\left(x_i, f\left(x_i\right)\right), s_j\left(s_j, f\left(x_j\right)\right)\ i \geq j \Leftrightarrow f\left(x_i\right) \geq f\left(x_i\right) \qquad (1)$$



(a) (b)

(c) (d)

Fig. 5. (a) Watrshed fingernail parts, (b) finger shape with fingernail plate overlaid, (c) distance calculation between finger edge-highest curvature point and all nail parts centroids along major axis plot, (d) drop distal free nail as noise, retain nail plate.

The location of the regions is important rather than the size of region in the image. All regions containing imposed minima are detected by watersheds' algorithm and output pictorially shown. This part of the segmentation process is subjective, supports programmatic detection of distal free nail object, together with fingernail plate area. The novel attempt combines the steps shown in Fig. 5. (a-d). A subsequent outcome of nail plate supports evaluation of region similarity. We find distal free nail area in the same direction of fingernail plate as a composite part, and then eccentricity property [6] is calculated. This defines it as a non-circular object and proves distal free nails are longer along width of finger segment, not relevant in nail plate area shape.

D. Ground Truth

Fingernails; the algorithm flow diagram with all the intermediate results of marker controlled watershed procedure is shown in Fig. 6 (a). Watershed nail parts examples are given in columns 2-3 of Fig. 6 (b). Manual region selection of complete fingernail plate and distal (free) nail area (edge) separately for all 200 finger images was carried out .Some of the result's as examples are given inside columns 4-5 of Fig. 6 (b), is considered to establish outcome of both methods [27, 17].

E. Assessment of Segmented Regions

Similarity is measured to determine correctness of semented areas in both the resultant images, the following numbers are computed. These measures gives us the total number of correctly matched, incorrectly matched, partially matched or mismatched pixels results in the corresponding objects (datasets/items), of ground truth regions and automatically identified watershed regions.

Table -1 Similarity of Nail Plates of Ground Truth and Watershed Segmentation Areas

Similarity	Images	Similarity	Images	Similarity	Images	Total Images
100-91 %	57	90-81 %	126	80-61 %	17	200

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Jaccard Distance (index) for set of resulting connected components regions are used to judge the outcome of segmented fingernail parts. There is a possibility of Jaccard distance measure on non-binary data (gray level) as long as the two image information matches exactly in units or/and in measures. Segmentation similarities for all the corresponding 200 finger regions are estimated. The result evaluation of correctly matched pixels between corresponding nail plates objects from two datasets is tabulated in Table 1. Nail plate similarity correctness is encouraging.

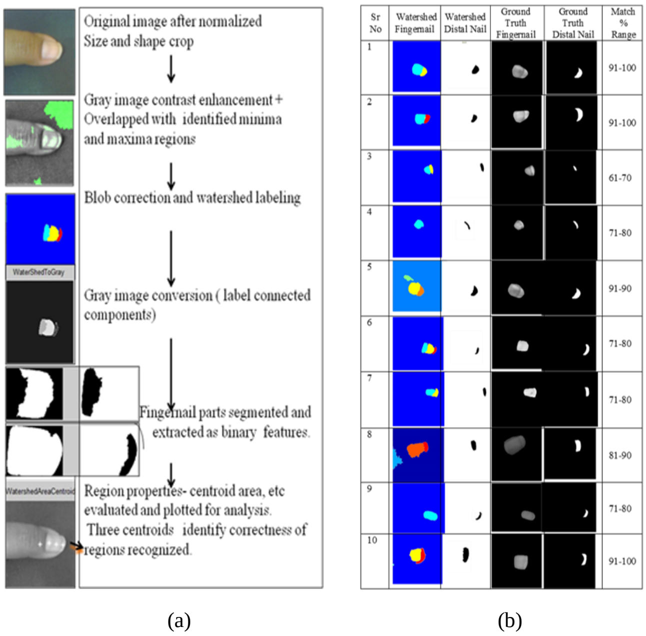

Fig. 6. (a) Algorithm of marker controlled watershed segmentation, (b) output examples of watershed method are in 2-3 columns, ground truth results are in columns 4-5, [27].

III. FINGERNAIL FEATURES

Most of the modern object detection algorithms use arbitrary or subjective groups to determine their respective parameters. However we settle down with subjective grouping of fingernail parts. The finger shapes are likely to be distorted due to effects of illuminations and reflections in spite of shadow corrections, reduced effects of surface curvatures and edges of intensity depths, etc. To correct generality inaccuracy we had to do lot of testing and provide potential algorithm. The feasibility process, prior information learning, gaining knowledge about shape, size, colour texture, finger geometry all support nail plate design by many folds. Method of informal learning with formal practical analysis, followed by additional fingernail feature extraction, plus parameter findings is all part of fingernail classification procedure. With the degrees of choice, we are able to accurately measure finger features, thereby reducing the probability of false acceptance easily.

A. *Shape Features*

Programmatically through watershed segmented, we reduce finger regions to 3-5 basis (with or without lunula and without distal free nail combination). The features like bound box (BB), filled area, perimeter, centroid, etc., are calculated. The major axis and minor axis are for shape evaluated of the segmented objects [14]. Bounding box gives filled area measure as a cross validation with width and height parameters. Centroid of distal free edge lies in closer proximity to highest curvature of finger boundary. The estimate $e= (f / b)$ as explained in Fig. 7(b), gives measure of roundness, to determine elongated shape attribute. This is used as another constraint to get proper nail plate perimeter as nail plates are not so stretched out in shapes. The centroid of lunula is calculated which lies closer to line of cuticle fold. This way, we clearly define lunula as an inclusive area of nail plate (hypothesis), near to one end point of major axis of nail plate [7, 18]. Basically shape features are primary discriminating parameters but there could be some variations in size because of small orientation differences. For this reason, region features has to be supported by contours and SVD.

B. *Context Based Boundaries*

According to theory of skin and fingernail, it is important to note that all nail plate shapes and finger shapes are not concentric to each other. Thus, it is understood that nail plate attributes do not directly help determine the same parameters for finger as an object. On the other hand, the nail plate information gives a good starting point for normalizing the centroids in image objects along with other geometric and statistical features. Likewise, the rotation of finger image is identified and corrected to get improved boundary and characterize perimeter of the nail plate correctly. The finger edges and nail plate edges are objects represented as context based geometric shapes using local points.

Contour Approximation is consequent to previous step of, features measures (example; finger bound box, filled area, etc.), the convex hull evenness is used for linking nail plate boundary results. The convex hull area is defined by set of all points of S in 2-dimensions $(n = 2)$, with digitized smooth boundary. A line connecting all vertices of convex sets contained in S form a smooth boundary. For N points $p1... pN$, the convex hull C can be expressed as given by Eq. 2, having complexity of $O(n*ln(n))$. The indices points, part of convex hull boundary is picked up as a vector list in anticlockwise order. Contour points retain the sophisticated geometry of nail boundary because extracted nail plate edge is not completely clear at lateral folds.

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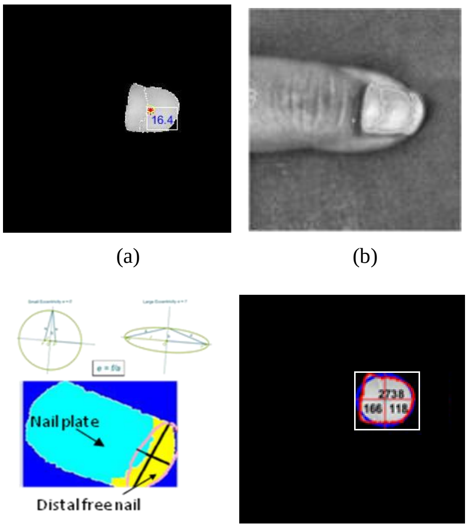


(a) (b)

(c) (d)

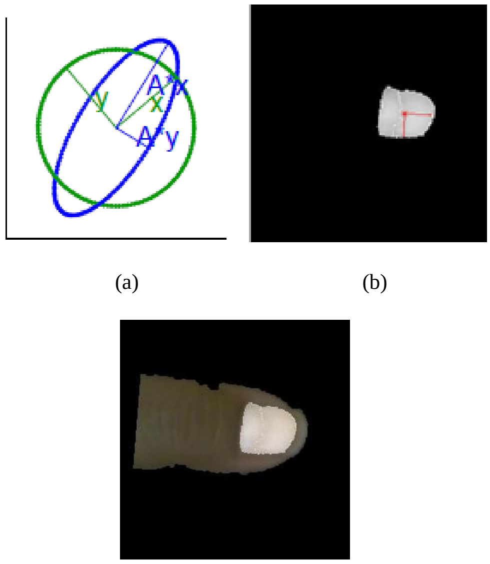
Fig. 7. Nail plate features (a) area, centroid, (b) boundary, (c) Measure of eccentricity *f* of area shapes (d) properties of nail plate; BB, perimeter, area, weighted centroid, edge, mean.

While this is done decidedly to process, correct smooth edges, we measure and mark the symmetrical line passing through the center points of nail plate (i.e., a geometric and weighted centroid). Ellipse fit with major and minor axis is measured and imposed. Smooth ROI extraction will further supports the additional SVD feature extraction besides shape and context based measures to augment it for more discriminant analysis (planned for better nail plate's recognition).

$$C \equiv \left\{ \sum_{j=1}^{N} \lambda_j \, p_j : \lambda_j \geq 0 \text{ for all } j \text{ and } \sum_{j=1}^{N} \lambda_j = 1 \right\} \quad (2)$$

C. SVD Translation

For effective results, a method that represents good features for matching the nail plate structure is tried out. SVD is algebraic method to get inrinsic properties that is stable in specified range. With possible emperial information learnt about the nail plate location, we begin to examine other attributes that are fundamental of the fingernail along its principal axes. Strategy of SVD is to deal with x-y axes symbol recognition as a factorization tool for image matrix approximation in nail plate design [13,15]. It helps compute two bases and certain singular values close to μ and σ. The term "singular value" in this context relates to the distance between a matrix and its calculated singular matrices. Properties of SVD that are invariant to scale space have supported the problem different sizes in matrix as characterized by Eq.3. Singular values considered here are covariance measurements in x-y axes; the maximum value is transformed into principal/major axis and the minimum value is along minor axis respectively as it is stable and does not vary to orientations. SVD of m x n matrix is calculated to define shape complexity using following equations.



(a) (b)

(c)

Fig. 8. (a) SVD approximation, (b) SVD plot on nail plate, (c) overlapped regions to verify.

$$A = \hat{U}\hat{\Sigma}\hat{V}^{*} \quad \text{or} \quad A = U\Sigma V^{T} \quad \text{if } m \geq n \quad (3)$$

$$U = [u_1, u_2, \cdots, u_m] \in R^{m \times m} \quad (4)$$

$$\Sigma = diag(\sigma_1, \cdots, \sigma_p) \quad (5)$$

$$V = [v_1, v_2, \cdots, v_n] \in R^{n \times n} \quad \text{where}$$

$$\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_p \geq 0 \quad \text{and} \quad p = \min(m,n) \quad (6)$$

In Fig. 7 (c), the axes of ellipse fit for nail plate distribution is shown. The *x* and *y* values are columns of $\hat{U}$ (are called the left singular vectors of *A*), and the orthonormal vectors *Ax* and *Ay* are multiples (*μ* and *σ*) of columns of *V* (are called the right singular vectors of *A*) of Eq. 3-6. The lengths of both axes are singular values computed for our recognition problem. The Singular Values Decomposition (SVD) of the square matrix *A* is defined as the square root of the Eigen Values of $A^{T}A$. The compounded covariance measures with shape features estimates acts as strong set of feature vectors for every pair of person fingers.

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D. Cross Validation

Relationship between distance function and discriminant function is as follows: select three minimum D_i^2. To establish the strength of classification model (choice of parameter selection), count the no of counts when *3-NN*, *2-NN* and *1-NN* are considered. Let $D\ (s_i,\ x)$ be distance measures between query x and stored/trained samples. The constraint of majority opinion, which is the maximum count of all the three ($k=\ 1,\ 2,\ 3$) is taken as criteria to classify. This, rules out the limitation of considering only one sample image for best match. The classifier system is designed to calculate *1 to k* specified closest neighbors for each class estimate validation. Which means the test/query sample will show maximum similarity to these data points present in the training set [14, 17].

Cross validation helps establish the categorization technique as results can vary. The general practice to divide the dataset into number of sub-samples of training and test is done to measure classifier outcome repeatedly with different combinations of elements. For every 5 samples data that we have for each finger, the selection is made in the following combination; for training { (1, 2, 3), (3, 4, 5), (5, 1, 2)} and for test {(4, 5), (1, 2), (3, 4) } respectively. The step is followed considers both thumb fingers of every object as an entity (20 people). The procedure judges simultaneously all attributes in the present feature set. Person recognition is ±1.5% for different grouping of datasets resulting to 87.5% on an average. Hence, this will result in almost appropriated classification result. Nearest neighbor rule is not a time consuming method unless dataset grows into a very large collection of information.

IV. RESULTS AND DISCUSSIONS

A. Result Evaluation

Confusion Matrix is a common method that gives overall picture of all the errors observed and gives correctly classified count along the diagonal of the matrix. Predicted label types are shown across a row per person. The reference data or the trained data is fixed to 3 samples a finger * 2 thumb fingers (total-6) represented along column. The best performance was observed for overall accuracy of 87.5% with grouping of 6-training and 4-test image combination for every class during modeling. The proposed classification is steady with various selections of training set images and their performances are definite for total dataset [21]. Evaluation of results shows that increase in training set gives increased performance rate. The ground truth for each class is labeled in supervised method and the number is fixed to 6 dataset for each class

B. Explanation

In Table-2. error matrix is tabulated to represent the accuracy for 4-test sample categorization. The diagonal elements in the matrix represent the number of correctly classified dataset of each class. That is the number of test images with a definite matching class name is obtained as same class name assigned (labeled-supervised learning) during supervised classification [19]. The diagonal elements show overall accuracy results. The off diagonal elements show total no of misclassified elements. Results are appropriate to the report illustrated and they are more than accurate enough, aimed at development of nail plates in suggested biometric method. The test assessment of all images with difference in object's orientation and non-distal nail plate biometric identification is encouraging.

The nail plate structure has supported SVD feature extraction besides shape and context based measures. SVD is a method for noise reduction in better singular values. Multiple features are more discriminative and augment nail plate's recognition. Suggested multiple features add to generalized outcome than those reported [22-25], when it concerns time complexity and difficult features selection. The k-NN classifier as a learning technique helps in validation choice of training and test dataset. Composite values are used to find '*k'* Nearest Neighbors with two fold validation. Classifier shows consistency amongst quality of nail plate regions extracted and is robust to noisy training dataset. The result of recognition of query/test samples is improved in support of biometric nail plate.

Table -2 Fingernail Recognition Accuracy for KNN Classification

	CLASSIFICATION RESULTS																						
	PERSON-20 DATASET	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	Row Total	Commission Error (%)
GROUND TRUTH	PER-1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	75
	PER-2	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	75
	PER-3	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	100
	PER-4	0	0	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	75
	PER-5	0	0	1	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	75
	PER-6	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	100
	PER-7	0	0	0	0	0	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	4	75
	PER-8	0	0	0	0	0	0	0	3	0	1	0	0	0	0	0	0	0	0	0	0	4	75
	PER-9	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	4	100
	PER-10	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	1	0	0	0	4	50
	PER-11	0	0	0	0	0	0	0	0	0	0	3	0	1	0	0	0	0	0	0	0	4	75
	PER-12	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	4	100
	PER-13	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	4	100
	PER-14	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	0	0	0	0	4	75
	PER-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	4	100
	PER-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	4	100
	PER-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	4	100
	PER-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	4	100
	PER-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	4	100
	PER-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	100
	Column Total	3	4	5	4	3	5	3	4	5	2	4	4	5	3	5	4	4	5	4	4	70 / 80	
	Omission Error (%)	75	75	80	75	100	80	100	75	80	100	75	100	80	100	80	100	80	100	100	100	OVERALL ACCURACY = 87.5%	

V. CONCLUSION

In this paper, we considered the problem of person identification based on fingers having nail plates with or without grown distal nail edges. The marker controlled watershed method is experimented to segment these parts to separate distal nail from complete nail plate object. The proposed segmentation algorithm is considered superior compared to other methods experimented as the results are better identifiable [9, 20] with all ROIs correctly identified. Method for effective set of features that represents better identity of fingernail plate structure is tried out. Classifier k-NN is not very recent but it supports statistical estimations as pattern recognizer and generalizes multi-class problems. And results are similar to human perception and easy to relevance. The combination of feature properties optimizes classification results. It becomes time consuming only when the database grows very large, otherwise proposed method gives almost predictable results. Since fingernail is not significantly explored, the situation makes it difficult to replicate an ideal biometric component in automated systems. In our future techniques, the focus will be to have large dataset which can measure, improved and generalize classifier performance.

VI. REFERENCE

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