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An adaptive approach to detection of dermatoglypic patterns of blind people using fingerprint classification

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Abstract: ***In this paper a study on dermatoglyphics pathology on complete blindness or suffering from other severe ophthalmic disorders based on the digital palmary impressions are discussed. Dermatoglyphic patterns in the hand are usually formed between the tenth and eighteenth weeks of gestation. After that their pattern remain unchanged except for an increase in size in parallel with general growth. In clinical medicine, patients with many chromosomal anomalies such as the trisomies, Patau's syndrome, Edwards' syndrome, (Down's syndrome), and the sex chromosomes (Turner's syndrome X0 and Kleinfelter's syndrome ,XXY) and deletion of the short arm of chromosome (Cri du Chat syndrome) are found to have abnormal dermatoglyphic patterns. The fingerprint patterns found in patients with leukaemia, early onset diabetes mellitus, alopecia areata, atopic dermatitis, rubella embryopathy, and chronic intestinal pseudo obstruction are found to be different from that of control group. These observations suggested that hereditary or environmental factors, acting in early gestation, may have played a role in the genesis of the disease. The aim of this study is to demonstrate the relation between presence of fingerprint patterns like whorl, arch etc.. in individual with their blindness. These studies have clearly demonstrated that even within the same geographical area, dermatoglyphic patterns though similar differ in proportions. A model of the fingerprint classification algorithm is discussed in this paper which categorizes the fingerprint according to their type. A standard approach for matching the input sample fingerprint with that present in the database and classify them is discussed in (K. Jain et al., 2007)[2]. As there are millions of fingerprints in database (for e.g criminal database) to match a person's fingerprint with existing fingerprints in the database takes large amount of time, fingerprint classification is considered as the first step in reducing the search time through large fingerprint databases and narrow down the search space into smaller datasets and hence speeds up the total response time of any AFIS(Automatic Fingerprint Identification System).***

Keywords : dermatoglyphics, fingerprint, FFT, Gabor filter

1. INTRODUCTION

All the humans are believed to have unique fingerprints. Fingerprint matching is done at two levels [1] called coarse level and fine-level.

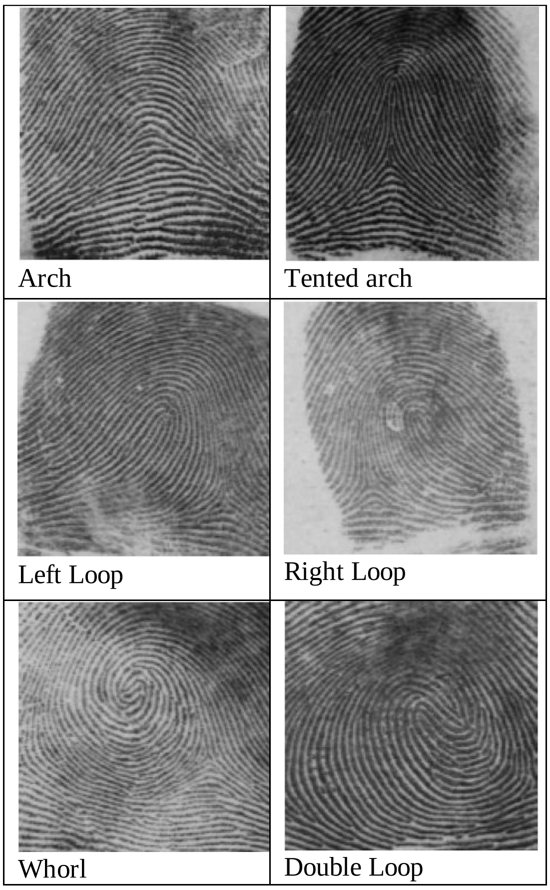

Figure 1. six classes of fingerprint (images from google)

At the coarse level, fingerprints can be classified into six main classes: arch, tented arch, right loop, left loop, whorl and twin loop, as shown in Figure. 1. The fine-level matching is performed by extracting ridge endings and branching points, called minutiae from a fingerprint image (see Fig. 2). Fingerprint verification is done in two phase. In the first phase (coarse level) the given fingerprint will be compared with all the fingerprints available in the database in which huge number of different type of fingerprints (left loop, right loop etc.,) will be present. In order to reduce the search time in this process first the database has to be filtered based on the type of fingerprint under consideration (i.e if it is left loop now the fingerprints with left loops only will be filtered from the database for the next step). In the second phase (fine level) fingerprint verification can be done by comparing the position of minutiae points.

(a) b)

Figure 2. Minute points a) Input image
b) minute point detection (images from google)

2. RELATED WORK

2.1 Fingerprint Classification

Each individual is believed to have unique fingerprints. Fingerprint matching is considered to be most reliable methods for identifying people. Kalle Karu et al [1] concentrated on the coarse-level classification of fingerprints. Their algorithm classifies the fingerprints by extracting singular points (cores and deltas). Their classifier is invariant to rotation, translation and small amounts of scale changes. [2] (K. Jain et al.) has made the first scientific studies on fingerprint classification area. He divided fingerprint into three classes namely: Loop, Arch, and Whorl. Galton's algorithm is then refined by increasing the number of classes into eight classes: Plain Arch, Tended Arch, Right Loop, Left Loop, Plain Whorl, Central Pocket, Twin Loop, and Accidental Whorl. It is observed that less than 5% fingerprints have arches in them. [3] (Maltoni et al.) grouped Arch and Tended Arch into one class. Their classification algorithm accuracy depends on the number of classes of fingerprints.
The fingerprint classification problem has been addressed by many researchers in the past. A syntactic method is presented by [4] (Rao *et al) T*he core and the delta points are used as points of registration in fingerprint matching by [5] (Srinivasan *et al)* whereas Poincare index is used to detect singular points in the image by Kawagoe and Tojo [6]. [7,8] Wilson *et al* have used a neural network to classify fingerprint images. [9] (Green & Fitz,) [10] (Sarbadhikari et al.,) and [11] (Park & Park) have used Fast Fourier Transform(FFT) to extract patterns from fingerprint images for fingerprint classification. In this paper we have developed a model in which the fingerprint images are divided into four sub images, and then a standard DFT is applied to each sub-image to extract the features under consideration.

2.2 Dermatoglyphics:

(Cummins and Midlo) [14] were the first to coin the term 'Dermatoglyphics' (from two Greek words- derma=skin, glyphe=carving). Their work is on Down's syndrome and showed that the hand with significant dermatoglyphic configurations would assist the identification of Mongolism in the newborn child. Sarah Holt [15] published the book *'The Genetics of dermal ridges'* and summarized the statistical distributions of dermatoglyphic patterns of the fingers and the palm in various people, both control and congenitally affected individuals. Their research focused on the identification of features of the palm that indicate the genetic likelihood of a mother giving birth to a Down's syndrome child and of twins. Schaumann and Alter's [16] published a book *'Dermatoglyphics in Medical disorders'* ***in*** which he discussed the dermatoglyphic patterns of various disease conditions . Rajangam S et al [17] studied dermatoglyphic patterns of Down's syndrome patients. Their study state that most of the patients have ulnar loops and abnormal dermatoglypic patterns such as simian crease, sydney line and patterns in the hypothenar and interdigital areas have occurred more frequently in these patients. Thomas Fogle [18] performed comparative Dermatoglyphic study between Downs syndrome patient and normal individuals. He found more occurrences of ulnar loops on index finger and radial loops on ring fingers in Down syndrome compared to normal individuals. Sardool Singh [19] studied Dermatoglyphics of schizophrenics; patients with Down's syndrome and mentally retarded males were compared with those of normal Australian Europeans. Their study showed increase in frequency of occurrence of ulnar loop in patients than normal. Matsuyama N, Ito Y [20] studied each fingerprint type (arch, ulnar loop, radial loop, and whorl) of the parents of children with Trisomy 21, born between 1965 and 1970 that was obtained from the Tokyo Medical and Dental University Hospital. Their statistical analysis shows more arches and fewer whorls in mothers of children with Trisomy 21 and fewer whorls and ulnar loops among fathers of Trisomy 21 children. Considering the mothers' fingerprints, they suspected that females with higher frequency of arches and lower frequency of whorls had stronger possibility of bearing Trisomy 21 babies.
Seltzer M.H [21] studied Fingerprints and palm prints of breast cancer patients. He concluded that women with 6 or more digital whorls are in danger of getting breast cancer and paved way that, analyzing digital dermatoglyphics plays a major role in identifying disease and its early preventive measure. Ravindranath R et al [22] studied total finger ridge count, absolute finger ridge count and finger print pattern of onset diabetes mellitus patients. Significant findings were: in males, with both hands combined and separately (i) an increase in radial and ulnar loops and arches (ii) A decrease in whorls. (iii) In females, an increase in ulnar loops and a decrease in whorls in the left hand were observed. Vera M et al [23] studied hand and palm dermatoglyphics of insulin-dependent diabetic children. The findings were compared with control group of similar racial distribution. They

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found an increase in the number of t'- axial triradii and ulnar loops in diabetic patients. R. S. Bali et al [24] studied dermatoglyphic patterns of diabetes mellitus patients of both sex. They concluded that there is an increase in the ulnar loop patterns among diabetes mellitus patients compared to control population. Barta et al [25] studied Dermatoglyphic features of adults with diabetes mellitus and found more occurrence of loop and arch patterns on the thumb of diabetes mellitus patients compared to healthy individuals. They also conducted a dermatoglyphics investigation to ascertain the reliability of dermatoglyphic as a predictive diagnostic tool for diabetes. Their study states that in female diabetics there is increased incidence of simple arch pattern. Increased incidences of TFRC(Total Finger Ridge Count) and AFRC (Absolute Finger Ridge Count) has been observed both in male and female diabetics. Increased incidences of ATD (angle formed by the triradius close to the wrist of the hand) angle is observed in male diabetics than in control. G.S.Oladipo et al [26] studied the characteristic dermatoglyphic patterns in prostate cancer. For this they took ATD (angle formed by the triradius close to the wrist of the hand) angles, DAT (angle formed by the triradius below the index finger)angles, A-B ridge and B-C ridge counts, axial triradii and digital triradii of the hands under study. Further [27] Gabriel S. Oladipo et al, studied the dermatoglyphic features of obese patients from the Ibibio ethnic group. Dermatoglyphic features such as digital and total ridge counts, DAT and ATD were assessed. The result shows more occurrence of arch pattern on the first right digits of obese males and females and more occurrences of ulnar loops in normal individuals. They also found the ATD and DAT angles on the right hands of male and female obese patients were significantly greater than those of normal male and female subjects. Udoaka et al [28], carried over their study on the digital print patterns of the Ijaw ethnic group using the students of University of Port Harcourt, Nigeria. They observed higher frequency of Ulnar loops (45.2%) in both sexes followed by Whorl pattern(32.6%), then the Arch pattern (14.28%) and the least occurrence of Radial loop pattern (7.4%),. the females. Ana Tarca, C.Barabolski [29] presented the results of a study on digitopalmary dermatoglyphices of patients diagnosed with infantile autism of country's eastern territory residents. The dermatoglyphic digito-palmary picture revealed a broad range of anomalies or distortions which differentiate significantly these people from the normal population.

Ana Tarca [30] conducted a complete digital dermatoglyphic investigations, on a group of delinquents from Moldova (North-East part of Romania). With the presence of some patterns in the fingerprints of delinquents from robbery to crime, they observed the correlation. Most of the digital distortions observed and found to be occurring on other European groups of delinquents, with the exception of two, namely: the extremely high ratio of the raketoid-type loops – on fingers IV and V especially – and that of the bilateral and individual monomorphism. P.S.Igbigbi and B.C.Msamati [31] carried out a cross-sectional study of healthy Kenyan and Tanzanian people and counted and classified the arches, loops, whorls and ridges in their fingers based on standard techniques. They conclude that, among the two East African populations the Tanzanians are dermatoglyphically closer to Mala- wins than Kenyans

B.R.Sontakke et al [32] studied the ridges of finger tips and palm in six Klinefelter's syndrome patients (47,XXY) and were compared with equal number of controls. They found that there is statistically significant increase in whorls (66.7%) to that of controls (35.0%) and decrease in loops in klinefelter's syndrome patients (31.7%) as compared to the controls (65.0%)

3. METHODOLOGY

3.1 Fingerprint Image Pre-processing

In our method, we consider classification of fingerprint images with five classes, Arch, Left Loop, Right Loop, Double loop and Whorl. The novel method consists of the following stages;

Any image has to be preprocessed. There are standard rule for pre-processing of an image before using it for further processes. In this we have adopted the following steps for pre-processing:

Image Pre-processing Steps:

1. Image Enhancement: The input fingerprint image is pre-processed on the spatial domain. Histogram equalization technique was applied for better distribution of the pixel values over the image to enhance the perceptional information. This allows areas of lower local contrast to gain a higher contrast without affecting the global contrast. The histogram of a fingerprint with double loop and after applying the histogram equalization is given in figure. 3a and figure 3b.

2. Image Binarization: In this step, an 8-bit grey level fingerprint image is transformed into a 1-bit image with 1-value for ridges and 0-value for furrows.

3. Image Thinning: This step aims to eliminate the redundant pixels of ridges till the ridges are just one pixel wide.

4. Image Segmentation: The objective of the fingerprint segmentation is to extract the region of interest (ROI) which contains the desired fingerprint impression. In the frequency domain, the image (250 x 250) was divided into four small processing blocks (128 x 128 pixels) and the 2-Dimensional Discrete Fast Fourier transform (FFT) was applied.

In order to classify the fingerprint broadly into the above considered classes, we have adopted the algorithm in figure 4.

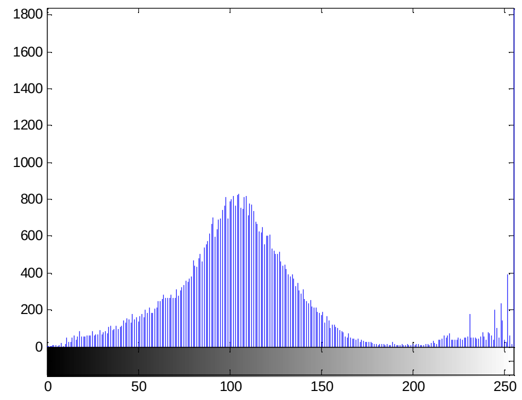

Figure 3 (3a) Original Histogram

The classification algorithm supports input fingerprint image in different formats, and the images size can be up to *(512 × 512)* pixels. In this we have taken (256x256) pixel image.

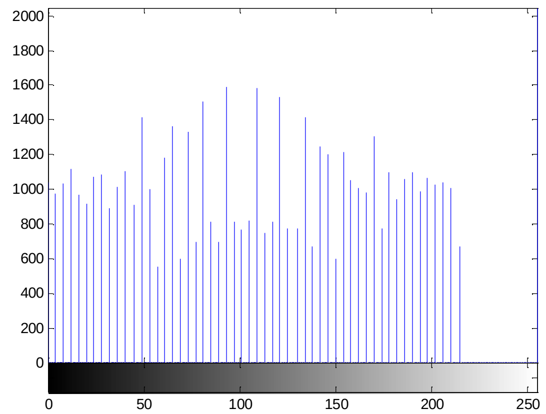

Figure 3: 3(b) after applying histogram equalization

3.2 Fingerprint Classification

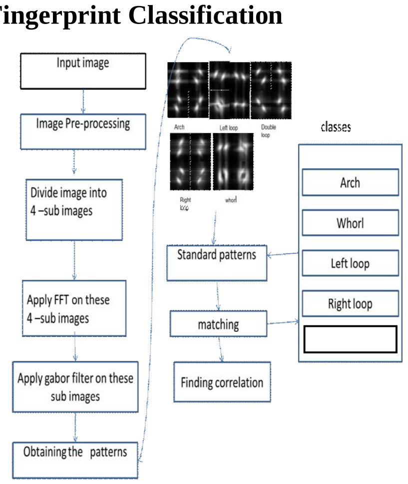

Figure. 4. Fingerprint classification algorithm

3.3 Division of Fingerprint image

At step (3), the input image is divided into four sub-images each of size 128 x 128 pixels. Figure 5 shows an example of the division process. Fingerprint partitioning provides the ability to process fingerprint image as four different blocks.

Fig. 5. A divided fingerprint image into four blocks (Input image was whorl)

3.4 Transformation into frequency domain

2D-FFT is a specific form of Fourier Transform used to convert images from spatial domain to frequency domain. [33] (Gonzalez et al., 2009). The FFT-based approach for estimating the frequency and direction of an image is an established method [34,10,11,12,33] (Sherlock et al., 1994; Sarbadhikari et al., 1998; Park & Park, 2005; Awad A.I et al , 2008; Gonzalez et al., 2009). One can add or subtract frequencies and recreate the original wave using and inverse Fourier Transform. Doing this with images or light waves helps to remove noises or find recurring patterns in an image. Applying FFT is able to clearly quantify the texture of fingerprint in various directions. Moreover, since these frequency features are global in nature, they are likely to be less sensitive to shift, rotation, and noise. In our method, a 2D-FFT is applied individually on each sub-image.

Fourier Transform decomposes an image into its real and imaginary components which is a representation of the image in the frequency domain. If the input signal is an image then the number of frequencies in the frequency domain is equal to the number of pixels in the image or spatial domain. The FFT and its inverse of a 2D image are given by the following equations:

$$F(X) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi(x\frac{n}{N})} \quad (1)$$

$$f(n) = \frac{1}{N} \sum_{n=0}^{N-1} F(x) e^{j2\pi(x\frac{n}{N})} \quad (2)$$

The DFT is the sampled Fourier Transform which means it does not contain all frequencies forming an image, but only a set of samples which is large enough to fully describe the spatial domain image. For a square image of size N×N, the two-dimensional DFT is given by:

$$F(k,l) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j) e^{-i2\pi\left(\frac{ki}{N}+\frac{lj}{N}\right)} \qquad (3)$$

where *f(i,j)* is the image in the spatial domain and the exponential term is the basis function corresponding to each point *F(k,l)* in the Fourier space. The equation can be interpreted as: the value of each point *F(k,l)* is obtained by multiplying the spatial image with the corresponding base function and summing the result. The basis functions are sine and cosine waves with increasing frequencies, *i.e.* *F(0,0)* represents the components of image which corresponds to the average brightness and *F(N-1,N-1)* corresponds to the highest frequency. In a similar way, the Fourier image can be re-transformed to the spatial domain. The inverse Fourier transform is given by:

$$F(a,b) = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} f(k,l) e^{i2\pi\left(\frac{ka}{N}+\frac{lb}{N}\right)} \qquad (4)$$

Where $\frac{1}{N^2}$ is the normalization term in the inverse transformation.

Gabor filter is a linear filter used for edge detection and texture analysis. Gabor filter set with a given direction gives a strong response for locations of the target images that have structures in the given direction. For instance, if a target image is made of a periodic grating in a diagonal direction, a gabor filter will give a strong response only if its direction matches the one of the grating. They offer the best localization of spatial and frequency information at the same time.

Figure 6 shows the Gabor filter applied FFT representation of all sub-images of a fingerprint in the Whorl class. The frequency pattern in each block shows a different pattern for each type of finger prints.

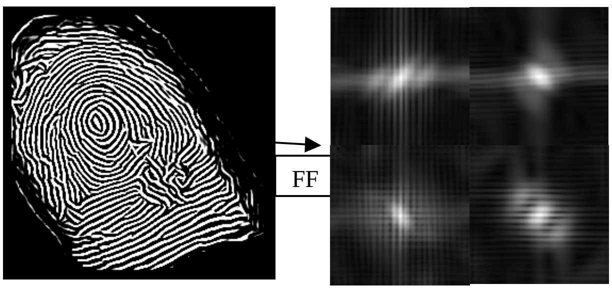

Fig. 6. Frequency domain representation for each sub image using 2D-FFT

3.5 Extraction of frequency patterns

In the next phase the patterns are extracted from the classified fingerprints. The pattern of each class is constructed by applying Gabor filters to the FFT outputs of four sub-images. Each finger print will thus have 4 patterns. The analysis can be done by taking these four patterns for each finger type. Initially standard patterns of the five standard classes are extracted once and stored. Next the fingerprint which is going to be classified is passed through this algorithm to classify to a particular class. In this the blind people finger prints are made to undergo all these processes. In the matching stage the 4-tuple of patterns of an input image is compared with the 4-tuples of the standard classes.

The following will affect the output of FFT (i) ridge direction, (ii) ridges frequency or pitch, and (iii) the brightness variation in the block. Figure 7 shows an example of the patterns corresponds to the FFT of control people and Figure 8 shows the patterns generated of blind people.

3.6 Patterns matching

The image obtained is converted to (256 x 256) size. We implemented the pattern matching of blocks by two methods, the Euclidian distance and the image correlation.

Patterns of control people

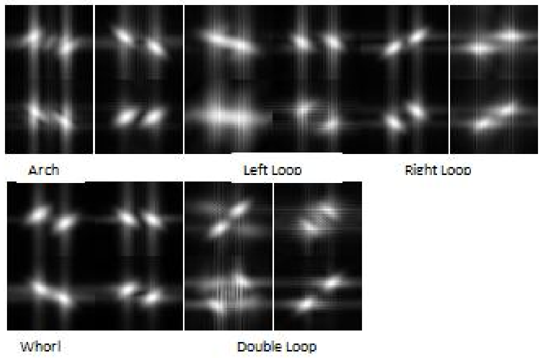

Fig. 7. Frequency transformation for each class (up left (Arch), up middle (Left Loop), up right (Right loop), down left (Whorl), down right (Double Loop))

Patterns of blind people

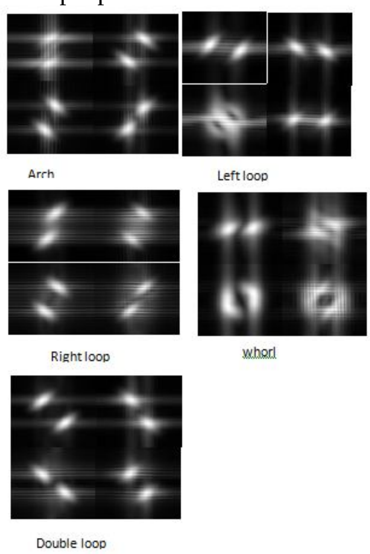

Fig. 8. Frequency transformation for each class (up left (Arch), up right (Left Loop), middle left (Right loop), middle right (Whorl), down left (Double Loop))

4.RESULTS

Tables 1 & 2 showed the percentage frequency distribution of the digital patterns in both the right and left hands of blind people and that of controls. Table 3 showed the total percentage occurrence in all the ten fingers in both sexes

Table 1a : Percentage frequencies of the Digital patterns of left hand of blind people

	LEFTTHAND				
	Big (i)	Index (ii)	Middle (iii)	Ring (iv)	Small (v)
LL	7.14	7.14	0	0	0
RL	50	42.86	78.57	57.14	64.29
W	21.43	21.43	7.14	21.43	28.57
DL	0	14.29	0	7.14	0
A	14.29	14.29	7.14	7.14	0

LL=Left Loop; RL=Right Loop; W=Whorl; DL=Double Loop; A=Arch

Table 1b: Percentage frequencies of the Digital patterns Right hand of blind people

	RIGHTHAND				
	Big (i)	Index (ii)	Middle (iii)	Ring (iv)	Small (v)
LL	57.14	50	78.57	57.14	64.29
RL	0	0	0	0	0
W	14.29	7.14	7.14	28.57	14.29
DL	7.14	21.43	7.14	7.14	21.43
A	21.43	21.43	7.14	7.14	0

LL=Left Loop ; RL=Right Loop; W=Whorl; DL=Double Loop; A=Arch

Table 2a: Percentage frequencies of the Digital Patterns of Left hand of normal people

	LEFT HAND				
	Big (i)	Index (ii)	Middle (iii)	Ring (iv)	Small (v)
LL	3.2	9.7	0	0	0
RL	45.2	37.1	59.7	38.7	74.2
W	27.4	29	22.6	50	14.5
DL	9.7	6.5	3.2	0	4.8
A	14.5	17.7	14.5	11.3	4.8

LL=Left Loop ; RL=Right Loop; W=Whorl; DL=Double Loop; A=Arch

Table 2a: Percentage frequencies of the Digital Patterns of Right hand of normal people

	RIGHT HAND				
	Big (i)	Index (ii)	Middle (iii)	Ring (iv)	Small (v)
LL	51.6	53.2	71	40.3	74.2
RL	0	6.5	1.6	3.2	3.2
W	27.4	21	11.3	43.5	14.5
DL	11.3	11.3	11.3	8.1	3.2
A	9.7	8.1	4.8	4.8	4.8

LL=Left Loop ; RL=Right Loop; W=Whorl; DL=Double Loop; A=Arch

Table 3: Percentage frequencies of Digital patterns of both blind and normal

	LL	RL	W	DL	A
blind	32.14	29.29	17.14	8.57	10
normal	30.48	26.94	26.29	6.61	9.52

5. CONCLUSION

This study has shown that the digital finger print patterns of blind people and of controls. There is 0% occurrence of Right Loop in right hand whereas in controls the occurrence of Right Loop is present in all right hand fingers, except in thumb (big finger). The occurrence of Right Loop in Left hand of blind people is more than that of controls. The occurrence of Whorl is found to be more in controls than that of blind people in both hands except in left hand small finger. The occurrence of double loop in index finger and small finger in the Right Hand and index finger and ring finger of Left Hand is more in blind whereas its frequency is less in that of controls. The occurrence of Arch is found to be more in right hand and less in left hand of blind people. The occurrence of Arch is more in left hand and less in right hand of control was observed.

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