

# Investigation of the Relationship between Fingerprint Pattern, Gender and Blood Group

Yousra Osman Abdalla Mohamed<sup>1</sup> and Dr. Elnazier Osman Hamza<sup>2</sup>

<sup>1</sup>Department of Biomedical Engineering, College of Engineering, University of Medical Sciences and Technology, Khartoum, Sudan  
*yassoosman@hotmail.com*

<sup>2</sup>Department of Radiology, University of Medical Sciences and Technology (UMST), Khartoum, Sudan  
*alnazier\_67@hotmail.com*

**Publishing Date: April 01, 2018**

## Abstract

The aim of this paper is to determine an accurate blood typing method, because knowing blood type of an individual is vital, hence the need for an accurate yet fast method of blood typing has arisen. Fingerprints are a great source for identification plus they provide effective and reliable evidence in law [1]. Some of fingerprints unique characteristics are that ridges formed during the fetal period do not change their shapes neither alignment throughout the lifetime until the skin is decomposed and the other one is that two fingerprints of either the same individual or two different individuals are never alike, they differ in their patterns alignment and features. Present study is an attempt to study distribution of thumbprint pattern among the subjects having different ABO and Rh blood group and to find any relation between their characters and blood groups using MATLAB. Factors relating to obtaining high performance feature point's detection algorithm, such as image quality, segmentation, image enhancement and feature detection have been studied. The study found that Majority of subjects were of blood group O. Distribution of right hand thumbprint showed high frequency of right, the distribution of left hand thumbprint showed high frequency of left loops, different pattern of thumbprints in individual fingers also showed some distinctiveness in relation to blood group.

**Keywords:** *Fingerprint, Thumbprint, MATLAB, Blood Type, ABO Systems.*

## 1. Introduction

Traditionally Blood typing tests have been conducted using conventional techniques such as slide and tube agglutination. Recently, automatic blood testing devices have been developed, but unfortunately are operational at blood centers and major hospitals only. These instruments have advantages such as high reliability and sensitivity. However, these advantages are not enough compared by the large size and high cost of the instruments which are major drawbacks, because on-site blood testing is an important requirement during an emergency case. Development of a portable, low-cost, and highly sensitive method for blood typing recognition is required to make on-site blood testing feasible[2].The dermal carvings or fingerprints appear for the first time on the human fingers, palm, soles and toes from 12th to 16th week of embryonic development and their formation gets completed by the 14th. The ridges thus, formed during the fetal period do not change their course or alignment during life, until destroyed by decomposition of the skin after death [3]. In practice, it is usually difficult to take a good quality fingerprint image, as these may be degraded and corrupted with noise due to many factors. This degradation can result in a significant number of pseudo ridges being created and actual minutiae being omitted, a much worse fingerprint can be obtained using ink methods [4].

## 2. Methodology

The quality of the collected fingerprint images is poor due to the presence of noise; direct feature extraction of such disturbed images will lead to false information. Thus, image enhancement has been done to reduce the noise and enhance the structure and clarity of ridges and valleys. In order to ensure the best results in minutiae extraction algorithms [5]. Minutiae extraction simply extracts important minutiae information such as core and delta points, and then stores the location and direction of each point; this technique is also used in some systems to detect duplicates [6].

### 2.1 Image Preprocessing

The idea behind image enhancement through preprocessing is simply to increase visibility of important details (such as ridges) and mark them as highly informative regions and mark others as too noisy for further processing. The input and output are gray-scale. There are five steps in image preprocessing:

#### Step one: Segmentation

Image segmentation is used to locate objects and boundaries such as lines and curves, in a fingerprint image there are foreground regions and background regions, the former shows the ridges and valleys which have high variance value while the latter shows regions that should be left out and have low variance values.

Segmentation separates the foreground regions from the background image for reliable extraction of minutiae. So the image was divided into several blocks for each block the gray scale variance was calculated, when the value was lower than the global threshold it was assigned to the background else it was assigned to the foreground [7].

#### Step two: Normalization

Some pixel operations were used so that the gray level values lies within a specific set of values. The fingerprint image was normalized so it has a predefined mean and variance this was essential because the image had distorted levels of gray values among ridges and valleys.

$$N(i, j) = M_p + \sqrt{V_p} (P(i, j) - M)^2$$

$$\text{if } P(i, j) > M$$

$$M_p - \sqrt{V_p} (P(i, j) - M)^2 \quad \text{other wise}$$

Where for a pixel P (i, j) the estimated mean and variances are M and V respectively,  $M_p$  and  $V_p$  are the desired mean and variance values [7].

#### Step Three: Contrast Enhancement

Is a process to enhance the contrast of a grayscale image by transforming its intensity values, usually a fingerprint image has different gray values for every pixel. It is desirable to have the gray value around a mean value.

Normalizing the image has improved the contrast between the ridges and valleys. It does not alter the shape of the original histogram.

#### Step Four: Ridge Orientation Estimation

The orientation image represents the local orientation of the ridges as a matrix of direction vectors. It is important because filtration depends on proper orientation.

Most of fingerprint recognition processes calculate the local ridge orientation of the fixed-size blocks instead of each pixel. The easiest way to do so was by computation of gradients. Image was divided in square blocks of  $r \times r$  (i.e.  $5 \times 5$ ). In each block, frequencies  $F[w]$  for  $w = [0, 1, 2, \dots, n]$  for  $n+1$  directions (i.e.  $w = 0 \dots 7$  for 8 directions) and average frequency were calculated. Then the difference between the frequency for each direction and average frequency was found. For every pixel the gradient and standard deviation (SD) for all directions were calculated [7].

If  $SD > \text{threshold}$ , then direction of ridges is the direction with maximum frequency.

$SD < \text{threshold}$ , then direction of ridges is calculated using average direction.

The orientation vector was calculated and gradient were found to be perpendicular to it; For a block of  $r \times r$  The gradient in the horizontal and vertical directions was found and given by  $\partial x(i, j)$  and  $\partial y(i, j)$  [6].

$$V_x(i, j) = \sum_{i+W/2}^{i-W/2} \sum_{j+r/2}^{j-r/2} 2 \partial x(p, q) \partial y(p, q)$$

$$V_y(i, j) = \sum_{i+W/2}^{i-W/2} \sum_{j+r/2}^{j-r/2} 2 \partial y(p, q) \partial x(p, q)$$

$$\theta(i,j)=0.5\tan^{-1}(V_y/V_x)$$

### Step Five: Frequency Estimation.

The ridge frequency at a point is the number of ridges per unit length along a line centered at [x, y] and at an angle to the ridge orientation.

First image has been divided into blocks of size  $W \times W$ . Then the gray-level values of all the pixels located inside each block along a direction with an angle to ridge orientation were found.

The ridge spacing was calculated by counting the number of pixels between a series of points in the projected waveform. Frequency was found by inverting ridge spacing, hence  $f(i,j) = 1/\text{ridge spacing}$ ,

For a block of certain size it was calculated by counting number of pixels between minutiae points.

### 2.2 Feature Extraction

Feature extraction aims to find endings and bifurcations from the skeleton image by examining the neighborhood of each ridge pixel using a  $3 \times 3$  window. Here a skeleton image was used, where the ridge flow pattern was eight-connected pixels.

The ridge pixels were divided into bifurcation, ridge ending and scar (or non-important details.) based on this process.

## 3. Results and Discussion

### Step 1



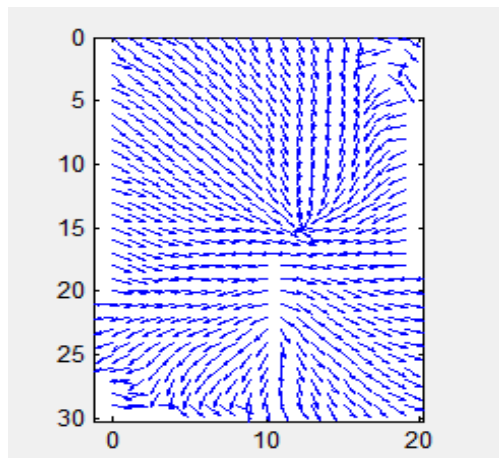
Figure 1: The Acquired Original Image

**Step 2**



**Figure 2: Image after Enhancement**

**Step 3**



**Figure 3: Ridge Orientation**

**Step 4**



**Figure 4: Image after feature extraction (core point)**

**4. Results**

According to three fingerprint experts a ground truth was established, the tables below compare the distribution of blood groups between ground truth and algorithm, results indicate that: Out of 906 students 348 (38.4) were male and 557 (61.5%) were female; the male-female ratio being 1:

1.6. Most common blood groups were ‘O’ positive (43%), ‘A’ positive (28.6%) followed by ‘B’ positive (17.6%). AB positive, O negative, AB negative and B negative were rarer, being present in 4.9%, 2.3% and 0.3% respectively. Males and Females had relatively similar incidence of AB (2.2% and 3%) and A (7.1 % and 11.9%) respectively.

**Table 1: Subjects distribution according to blood group and gender**

Blood group	Male		Female		Total	
	No. of subjects	percentage	No. of subjects	percentage	No. of subjects	percentage
A	94	10.38%	182	20.09%	276	30.50%
B	64	7.06%	108	11.92%	172	19.00%
AB	20	2.21%	28	3.09%	48	5.20%
O	170	18.76%	240	26.49%	410	45.30%
Total	348	38.41%	558	61.59%	906	100.00%

**4.1 Right Hand Thumb**

According to experts, Loops are most commonly obtained fingerprints (45.58%) followed by whorls (33.44%).

Arches and left loop were least found (Table 2). In all the blood groups, proportion of loops was highest.

**Table 2: Right hand thumbprint patterns distribution along different blood groups**

Blood Group	Arch		Loops		Whorl		Double		Total	
	Total Number	Percentage %	Total Number	Percentage %	Total Number	Percentage %	Total Number	Percentage %	Total Number	Percentage %
A-	7	0.77	25	2.76	13	1.43	9	0.99	54	5.96
A+	35	3.86	60	6.62	90	9.93	37	4.08	222	24.50
AB-	0	0.00	4	0.44	1	0.11	0	0.00	5	0.55
AB+	3	0.33	19	2.10	18	1.99	3	0.33	43	4.75
B-	0	0.00	1	0.11	9	0.99	1	0.11	11	1.21
B+	9	0.99	85	9.38	47	5.19	20	2.21	161	17.77
O-	0	0.00	7	0.77	6	0.66	3	0.33	16	1.77
O+	28	3.09	212	23.40	119	13.13	35	3.86	394	43.49
<b>total</b>	<b>82</b>	<b>9.05</b>	<b>413</b>	<b>45.58</b>	<b>303</b>	<b>33.44</b>	<b>108</b>	<b>11.92</b>	<b>906</b>	<b>100.00</b>

#### 4.2 Left Hand Thumb

Left Loops were most commonly obtained fingerprints (42.4%) followed by whorls (31%). Arches and left loop

were found in 25% and 1.6% respectively (Table 5.3). In all the blood groups, proportion of loops was highest

**Table 3: Distribution of left hand thumbprint patterns along different blood groups**

Blood Group	Arch		Loops		Whorl		Double		Total	
	Total Number	Percentage %	Total Number	Percentage %	Total Number	Percentage %	Total Number	Percentage %	Total Number	Percentage %
A-	3	0.33	38	4.19	10	1.10	3	0.33	54	5.96
A+	44	4.86	60	6.62	96	10.60	22	2.43	222	24.50
AB-	2	0.22	2	0.22	1	0.11	0	0.00	5	0.55
AB+	6	0.66	19	2.10	13	1.43	5	0.55	43	4.75
B-	0	0.00	4	0.44	5	0.55	2	0.22	11	1.21
B+	18	1.99	96	10.60	30	3.31	17	1.88	161	17.77
O-	2	0.22	4	0.44	3	0.33	7	0.77	16	1.77
O+	46	5.08	199	21.96	119	13.13	30	3.31	394	43.49
<b>total</b>	<b>121</b>	<b>13.36</b>	<b>422</b>	<b>46.58</b>	<b>277</b>	<b>30.57</b>	<b>86</b>	<b>9.49</b>	<b>906</b>	<b>100.00</b>

#### 5. Conclusion

This study revealed that there were an association between distributions of thumbprint (dermatoglyphic) pattern and blood groups the general distribution pattern of the primary thumbprint was of the same

order in individuals with A, B, AB and O blood group i.e. High frequency of loops, moderate of whorls and low of arches the same findings were seen in Rh-positive and Rh-negative individuals of ABO blood group.

The correlation was more consistent for blood group A and loops, arches were more in blood group AB in present study. We concluded that there was an association between distribution of fingerprint patterns, blood group and gender and thus prediction of gender and blood group of a person is possible based on his/her fingerprint patterns.

## References

- [1] Landsteiner, K., 1900. Zur Kenntnis der antifermentativen, lytischen und agglutinierenden Wirkungen des Bluteserums und der Lymphe. *Zbl bakt*, 27(10), pp.357-362.
- [2] Quinn, J.G., O'Kennedy, R., Smyth, M., Moulds, J. and Frame, T., 1997. Detection of blood group antigens utilizing immobilized antibodies and surface plasmon resonance. *Journal of immunological methods*, 206(1), pp.87-96.
- [3] Hong, L., Wan, Y. and Jain, A., 1998. Fingerprint image enhancement: Algorithm and performance evaluation. *IEEE transactions on pattern analysis and machine intelligence*, 20(8), pp.777-789.
- [4] Tukur, A., 2015, Fingerprint Recognition and Matching using Matlab.
- [5] Hong, L., Wan, Y. and Jain, A., 1998. Fingerprint image enhancement: Algorithm and performance evaluation. *IEEE transactions on pattern analysis and machine intelligence*, 20(8), pp.777-789.
- [6] Tukur A., 2015. Fingerprint Recognition and Matching using Matlab. *The International Journal of Engineering and Science (IJES)*, vol 4, pp1.
- [7] Solanki, K. and Patel, C. (2013). Biometric Key Generation in Digital Signature of Asymmetric Key Cryptographic To Enhance Security of Digital Data. *International Journal of Engineering Research & Technology (IJERT)*, 2(4).