Image Quality, Performance, and Classification – the impact of finger location

Michael E. Brockly, Stephen J. Elliott

Abstract—**The purpose of this paper is to provide additional analysis of image quality and Henry Classification on Finger location on a single sensor. One hundred and sixty nine individuals provided six impressions of their left index, left middle, right index, and right middle fingers. The results show that there is significant difference in image quality, Henry classifications, and zoo animal distribution across the four finger locations under study. The results of this research show that location is an important consideration when developing enrollment best practices for single print systems.**

Index Terms—**Biometrics, Fingerprint Recognition, Henry Classifications**

I. Introduction

IN 1888, Edward Henry developed a classification schema for pattern types of fingerprints. There are three main types of classification; loops, whorls, and arches [1]. Additional subcategories can also be created, and for the purposes of this paper, we use six classifications generated by a commercially available Henry Classifier. These are left loop, right loop, plain arch, tented arch, whorl and scar. This is a similar classification approach as noted in [1]. As noted in [2] and [3], the distribution of Henry classifications are not homogenous. For example, the predominant Henry Classification in [3] for the left thumb and left index is the right loop (51.26%, 34.61% of occurrence respectively); the right thumb and right index is left loop (58.44%, 39.00% of occurrence respectively). In a recent study, the most frequent pattern was the ulnar loop, both in the general population and the gender distribution [4]. The motivation of this work is to add to the body of literature on the distribution of these classifications, across different fingers, and to expand the zoo-plot methodology proposed by [5].

II. Research Questions and Motivation

The purpose of this paper to understand how the Henry classification, image quality, minutiae count and performance are all impacted by finger location. There are three motivating factors – the first is to update a previous paper [2], that examined a similar problem and used the same sensor. Our paper differs in that a different population was used, and different classification, quality and performance tools are implemented. Furthermore, in that paper, performance was shown by a series of detection error tradeoff curves, in this paper, we are evaluating the performance of the specific finger locations by looking at the zoo plot analysis – the second motivation behind this paper. This is a relatively new approach in visualizing data in biometric systems. A detection error tradeoff curve typically used in the biometric literature presents a graphical image of biometric performance, but only at a global level. A zoo plot analysis will examine whether there are any differences in a user's genuine and impostor match scores across the Henry Classification, Finger Location, and Image Quality. In order to calculate a zoo plot, the methodology outlined in [5] was applied. The zoo plot outputs four different "animals" called chameleons, phantoms, doves, and worms. Each of these animals has specific traits, or characteristics based on their respective match scores. Subjects that are chameleons are characterized by high match scores, and therefore they are hardly cause false rejects, but are likely to cause false accepts. Conversely, phantoms lead to low match scores, regardless of who they match against. The other two animals are worms – these animals are the worst users, and typically cause a proportionately high numbers of errors. The best users are worms, who have high matching scores as well as low impostor scores. A frequency of each animal's occurrence by classification and location will be presented in the results section. The third motivation is to add to the current body of knowledge relating to the Henry Classification, and to gain a better understand in the issues relating to finger location, so that the results of this paper can be fed back into the development of the Human Biometric Sensor Interaction model [6]. The remainder of the paper covers the experimental methodology, results, and finally conclusions and recommendations for future work.

III. Methodology

A. Data collection

This study used data collected from a larger study [7]. This dataset was sub-sampled to one sensor, and only those subjects that provided six successful impressions on the left index, left middle, right index, and right middle were included. A total of 169 subjects are included in the analysis, the demographic information is shown below in Table I:

TABLE I

DEMOGRAPHIC INFORMATION

Total Population	Male	Female	N/A
169	118	49	2
Self-disclosed information	Office	Manual	N/A
169	148	16	5

The sensor used was the Identix® DFR-2080. Sensor information with compliance to standard ISO/IEC JTC 1 N-29120 standard in Table II:

TABLE II

SENSOR INFORMATION

Manufacturer:	Model:	Dimensions:
Identix	DFR-2080	76 x 38 x 83 mm
Resolution:	Type:	Platen size:
500 dpi	Optical Touch	15 x 15 mm

The breakdown of subjects by age is shown in Figure 1.

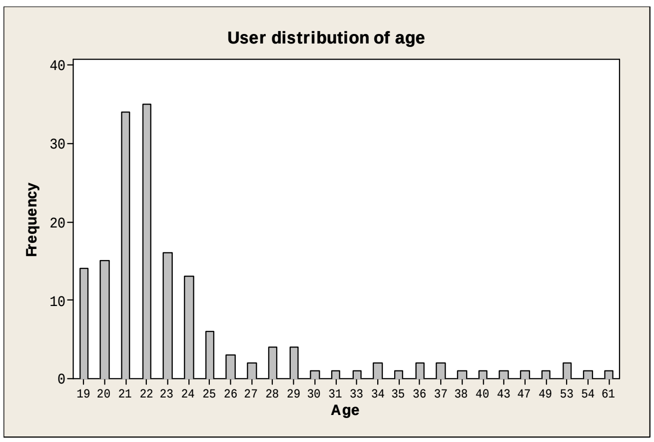

Fig 1: Distribution of Age

The variables of interest in this study were minutiae count, quality score, Henry classification, and the metrics associated with the zoo plot analysis. The minutiae count and image quality was derived through using a commercially available tool (Aware M1 pack version 3.0.0). The Henry classification was extracted, and matching performance calculated using Neurotechnology Megamatcher version 4.0.0. The zoo plots were calculated using Performix with the output from the matcher.

IV. RESULTS

The results section will answer the following research questions: (1) how does the Henry classification change across finger locations; (2) does image quality change across the finger locations; (3) does minutiae count change across the finger locations; (4) does finger location impact performance (presented through the use of the zoo animal model developed by [5]).

A. *Henry Classification across finger locations.*

A total of 4,080 samples were processed, with the Henry classifications across the finger locations noted in the table below.

TABLE III

HENRY CLASSIFICATION BY FINGER LOCATION

Henry	LI		LM		RI		RM	
	No	%	No	%	No	%	No	%
Whorl	322	31.6	235	23.0	301	29.5	212	20.8
Left Slant Loop	421	41.3	675	66.2	259	25.4	46	70.0
Right Slant Loop	190	18.6	35	3.4	366	35.9	714	4.5
Tented Arch	54	5.3	46	4.5	24	5.2	5	2.8
Plain Arch	32	3.1	24	2.4	39	3.8	14	1.4
Scar	1	0.1	5	0.5	2	0.2	5	0.5

These observations are in line with previous studies that examined the distribution of Henry Classifications. For example in [4], the distribution of index fingers for whorls is 28.8% (31.6% for this study on the left index; 29.5 on the right index). In terms of ranking, loops for the index finger comprise of 43.4% which is approximately in line with the findings of this study.

A. *Image Quality*

Image quality can impact the performance of a fingerprint recognition system. Figure 2 shows interval plot of image quality across the four finger locations.

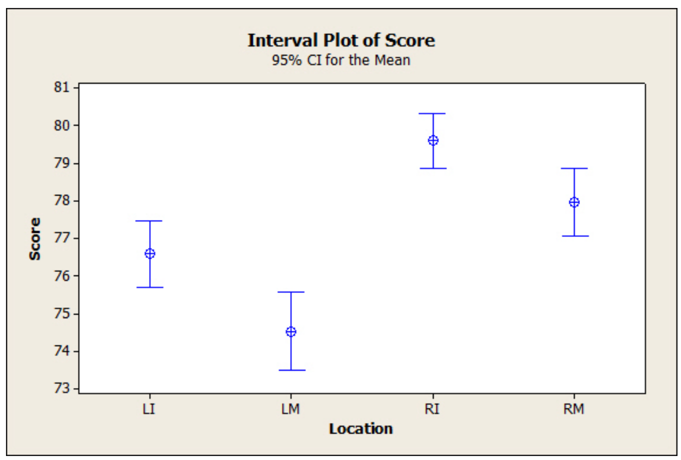

Fig 2: Image Quality vs. Finger Location

The results show that image quality differed between the finger locations; one-way ANOVA $F_{(3,4076)} = 22.01$, $p<0.001$.

B. *Minutiae count across finger locations*

The process was repeated to establish whether there were any significant differences in minutiae count across Henry Classifications and finger location. The minutiae count differed between Henry Classifications; one-way ANOVA $F_{(5, 4074)} = 94.47$, $p=<0.001$, with the grouping information using the Tukey HSD method shown below in Table IV.

TABLE IV
HENRY CLASSIFICATION BY FINGER LOCATION

Henry Class	Grouping		
Whorl	A		
Scar	A	B	
Left Slant Loop		B	
Tented Arch		B	
Right Slant Loop		B	
Plain Arch			C

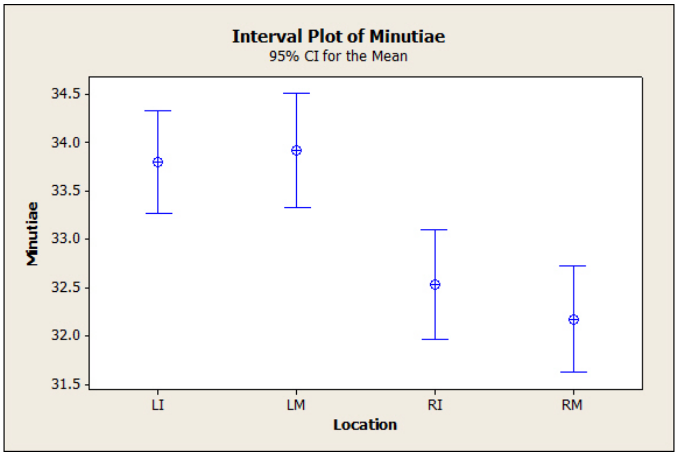

Fig 3: Minutiae vs. Finger Location

Figure 3 shows an interval plot of the number of minutiae across finger locations. Image quality differed between the finger locations; one-way ANOVA $F_{(3,4076)} = 9.62$, $p<0.001$. The grouping information using the Tukey HSD is shown in Table V. The means that do not share a letter are significantly different.

TABLE V
HENRY CLASSIFICATION BY FINGER LOCATION

Henry Class	Grouping	
Left Index	A	
Left Middle	A	
Right Middle		B
Left Middle		B

C. Performance at different finger locations

Figure 4 shows the detection error tradeoff curve for all finger locations. This particular dataset had an Equal Error Rate of 0.30%. Figure 5 shows the zoo plot and the spread on both axis indicating that there are a set of poorly performing users. This can be seen in more detail in Figure 6, where the distribution of animals by finger location is illustrated. There is a high frequency of chameleons and doves – especially in the right index location, followed by left index.

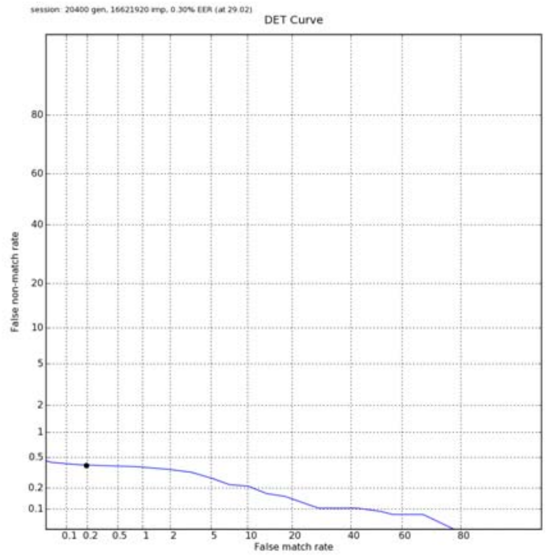

Fig 4: Detection Error Tradeoff Curve

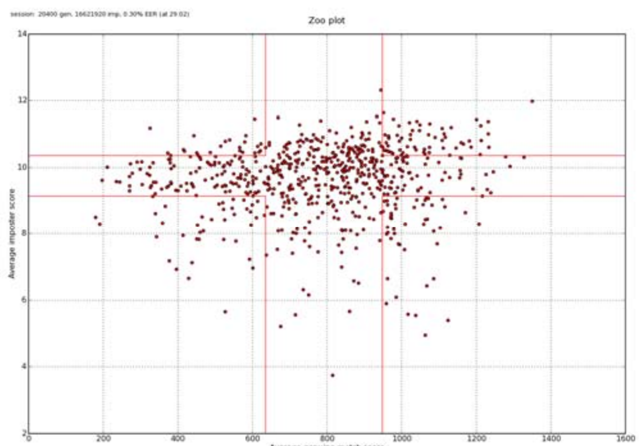

Fig 5: Zoo Plot

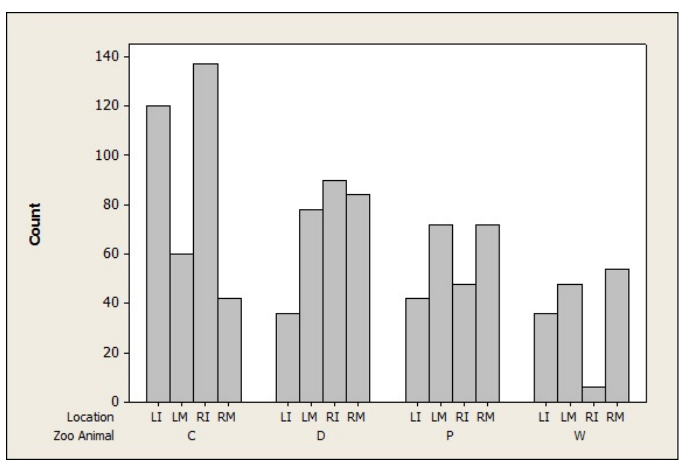

Fig 6: Distribution of zoo animals across finger location

I

V. CONCLUSIONS

We can see that finger location has a contributing factor to performance (the zoo plots being an indicator of this). There are also differences in minutiae counts across the four finger locations. Future research should investigate whether these results hold for other fingerprint sensors with the same population – for example, are the Henry Classifications consistent across different types of different sensors. In addition, the zoo plots provide a deeper understanding of performance, and therefore, understanding the characteristics of these animals, and how poor performance, especially in the case of worms and chameleons can be addressed. A deeper analysis of the genesis of the poor performing animals is probably justified.

REFERENCES

[1] J. Wayman, A. K. Jain, D. Maltoni, and D. Maio, "An Introduction to Biometric Authentication Systems," in *Biometric Systems*, J. Wayman, A. Jain, D. Maltoni, and D. Maio, Eds. London: Springer, 2005, pp. 1-20.

[2] M. R. Young and S. J. Elliott, "Image Quality and Performance Based on Henry Classification and Finger Location," in *2007 IEEE Workshop on Automatic Identification Advanced Technologies*, 2007, pp. 51-56.

[3] H. Jarosz, J. C. Fondeur, and X. Dupré, "Large-scale identification system design," in *Biometric Systems: Technology, Design and Performance Evaluation*, London: Springer-Verlag, 2005, pp. 263–287.

[4] M. D. Nithin, B. M. Balaraj, B. Manjunatha, and C. M. Shashidhar, "Study of fingerprint classification and their gender distribution among South Indian population," *Journal of Forensic and Legal Medicine*, vol. 16, pp. 460-463, 2009.

[5] N. Yager and T. Dunstone, "The biometric menagerie.," *IEEE transactions on pattern analysis and machine intelligence*, vol. 32, no. 2, pp. 220-30, Mar. 2010.

[6] E. P. Kukula, M. J. Sutton, and S. J. Elliott, "The Human–Biometric-Sensor Interaction Evaluation Method: Biometric Performance and Usability Measurements," *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 4, pp. 784-791, Apr. 2010.

[7] S. Modi, "Analysis of Fingerprint Sensor Interoperability on System Performance," Purdue University, 2008.

Michael E. Brockly is currently an undergraduate researcher in the biometrics standards, performance and assurance laboratory at Purdue University. His previous work includes research into dynamic signature verification and its effects on the human-biometric sensor interaction model. He is currently working on further improvements of the HBSI model and seeks to adapt it to more modalities.

Stephen J. Elliott is currently a faculty member in the Department of Technology, Leadership and Innovation. His interests include the testing and evaluation of biometric systems.