Gender Determination using Fingertip Features

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ABSTRACT: Several previous studies have investigated the gender difference of the fingerprint features. However, regarding to the statistical significance of such differences, inconsistent results have been obtained. To resolve this problem and to develop a method for gender determination, this work proposes and tests three fingertip features for gender determination. Fingerprints were obtained from 115 normal healthy adults and comprised of 57 male and 58 female volunteers. All persons were born in Taiwan and were of Han nationality. The age range was18-35 years. The features of this study are ridge count, ridge density, and finger size, all three of which can easily be determined by counting and calculation. Experimental results show that the tested ridge density features alone are not very effective for gender determination. However, the proposed ridge count and finger size features of left little fingers are useful, achieving a classification accuracy of 75% (P-value<0.001) and 79% (P-value<0.001), respectively. The best classification result of 86% accuracy is obtained by using ridge count and finger size features together. This paper closes with a discussion of possible future research directions.

KEY WORDS: Gender determination; Fingerprint; Dermatoglyphic; Sex determination

INTRODUCTION

Many human body features have been used to estimate sex/gender. Some of recent examples include foot print ratio,[1] metatarsals,[2] humerus,[3] long bones of the arm,[4] foot shape,[5] femoral head,[6] foot and shoe dimensions,[7] patella,[8] teeth,[9] and radial and ulnar bone lengths.[10] Due to their uniqueness and immutability, fingerprints are also one of the most commonly employed biometric features.[11] Fingerprints have become increasingly popular for personal identification and verification in applications including banking security and physical access control. Despite many well developed fingerprint matching techniques and a wide range of biometric applications, a reliable fingerprint based gender determination method does not seem to be available.

Although it has been found that males tend to have more ridge counts than females,[12-15] inconsistent results have been obtained with regard to the statistical significance of this sex difference.[16-18] It has also been shown that women tend to have a higher ridge density (ridge counts divided by the size of the corresponding fingertip area) than men but the sex determination accuracy of this feature does not seem to be very satisfactory.[19]

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The size of the fingertip has a strong relationship to the values of ridge counts and ridge density. If males have more ridge counts and smaller ridge densities than females, then the finger size difference between males and females should be more significant than the features of ridge count and ridge density.

This work introduces and investigates gender determination methods based on finger related features. To achieve this goal, a new ridge count criterion is proposed that accounts for more ridges than the conventional approach. In addition, instead of comparing the total ridge count of the hands, ridge count on a finger-to-finger basis is explored. Finally, the potential of finger size for sex discrimination is investigated. Experimental results demonstrate the effectiveness of the proposed features for gender determination.

METHODOLOGY

In this work, fingertip images were obtained from 115 normal healthy adults comprised of 57 male and 58 female volunteers. All persons were born in Taiwan and were of Han nationality. The age range was18-35 years.

Traditionally, fingerprints have been extracted by creating an inked impression of the fingertip on paper. However, this acquisition procedure is sensitive to environmental factors and skin condition.[20] Since many fingerprint images acquired this way are of poor quality, this work relies on fingertip images captured using a digital camera (Canon G3, resolution 2272 × 1702 pixels). **Figure 1** gives an example of such an image. (Based on our experience, taking pictures of thumbs is much more time consuming than other fingers. As such, this work has not studied images from thumbs.)

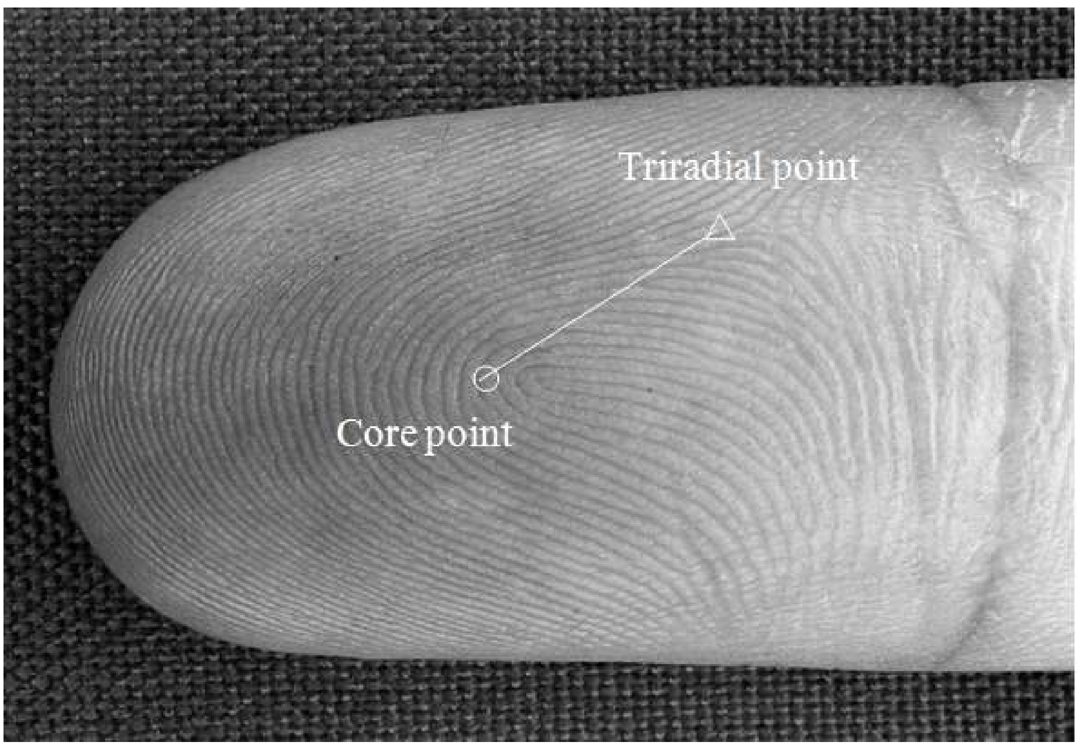

Figure 1: Triradial and core points

Ridge count is traditionally defined as the number of ridges intersected by a line between the triradial points (also called the delta point) and the core point. The core is the topmost point of the innermost curving ridge and the triradius is defined as the meeting place of three dermal lines that make angles of approximately 120° with one another, as shown in **Figure 2**. This ridge count measure has several weaknesses. First, some fingers have no triradial points and other fingers may have more than one. Second, due to the randomness of the locations of the core and triradial points and the fact that the line that joins these two points only covers a small portion of the fingertip, it is questionable whether the traditional ridge count measure can reliably represent the overall ridge count of the finger. To remedy these problems, the ridge count feature used in this work is determined by the following procedure:

1. From the image captured by the digital camera, segment the finger by finding the skin-color region of the image.
2. Based on the boundary of the segmented finger region, determine a symmetrical axis for the finger.
3. Draw a line passing through the core point that is perpendicular to the symmetrical axis determined in the previous step.
4. Determine the line segment of interest by first finding the intersection of the line drawn in the previous step and the segmented finger region obtained in step 1.
5. Shorten the line segment of interest by removing 5% of its length from both ends of the line since in such regions the finger surface often varies rapidly, making accurate ridge counting rather difficult.
6. Determine the ridge count by counting the number of ridges along the line segment from the previous step.
7. Determine the length of the line segment of interest. Note that this work uses this length to characterize the size of the finger.

With the exception of core point detection and ridge number counting, the procedure can be executed automatically using a computer program. The line segment employed in this work, as shown in **Figure 2**, intersects the entire finger. Consequently, the number of ridges obtained by the proposed approach is considerably larger than that found conventionally. It is posited that the proposed ridge count measure can characterize the ridge count of the entire finger and offers a more meaningful metric.

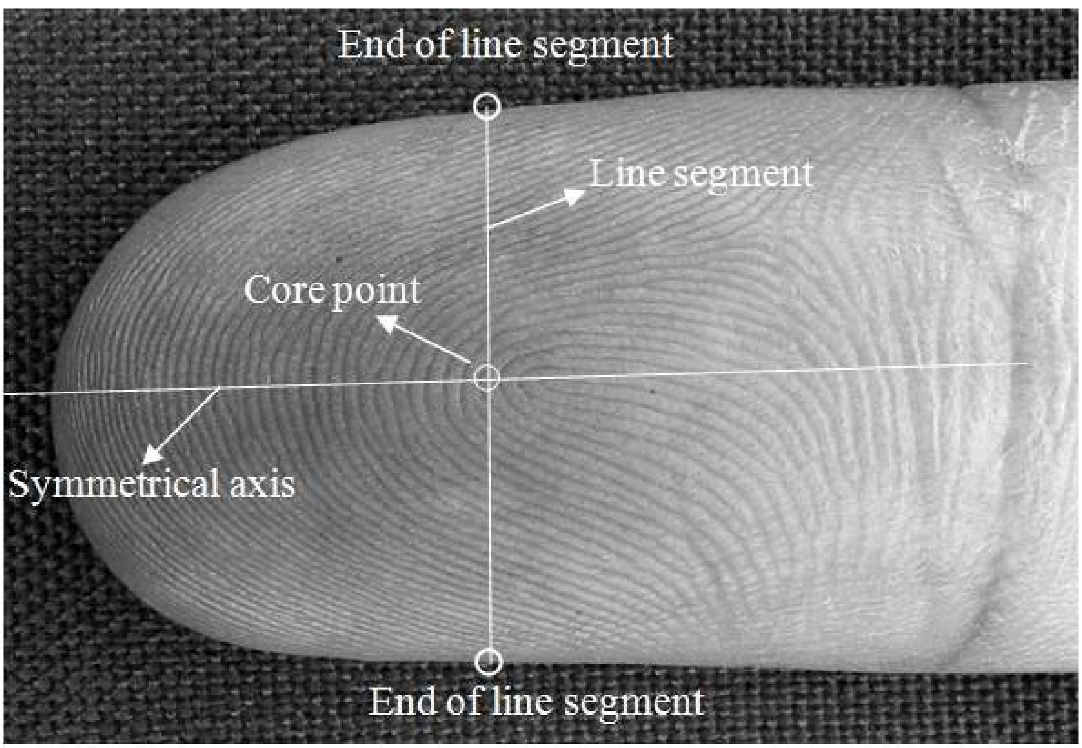

Figure 2: The line of interest

RESULTS

The proposed features were tested by performing a series of gender discrimination experiments. With the multilayered perceptron (MLP) as the classifier,[21] the dataset was divided into training, validation and testing subsets with an 8:1:1 ratio. The training subset is used to adjust the connection weights of the MLP, the validation subset is used by the early-stop technique to avoid overfitting, and the testing subset is used to characterize the generalization accuracy of the MLP. For the sake of reliability, the training process was repeated 1000 times using randomly partitioned training, validation and testing subsets. The sample mean and standard deviation values of the testing subset classification accuracy are reported.

In presenting the experimental results, the index, middle, ring and little fingers of the right and left hands are represented by R_2, R_3, R_4, R_5, L_2, L_3, L_4 and L_5, respectively. Symbols m_R , m_L and m_B are used to signify the average of these fingers for right, left and both hands, respectively. In specific, they can be calculated by the following equations:

$$m_R = ¼ (R_2 + R_3 + R_4 + R_5)$$

$$m_L = ¼ (L_2 + L_3 + L_4 + L_5)$$

$$m_B = ½ (m_R + m_L)$$

The first part of the experiment tests the effectiveness of separate features, i.e., ridge count, ridge density, and finger size for gender determination. The results are summarized in **Tables 1, 2** and **3**. Comparing the results of these three tables indicates that the finger size feature gives the best results. In particular, as demonstrated by **Table 3**, all of the tested finger size features achieve statistical significance ($P <$ 0.001, two-sided *t*-test) and the best classification accuracy is about 79%. In addition, as shown by **Table 1**, the tested ridge count features all yield statistically significant results. However, their classification accuracy is inferior to that of the finger size feature. As shown by **Table 2**, none of the tested ridge density features achieve statistical significance and the best classification accuracy is only about 55%.

The second part of the experiment investigates the potential of improving the classification accuracy by combining features. Specifically, the first feature set consists of ridge count and finger size features. As shown by **Table 4**, this feature set improves the classification accuracy in contrast to the results obtained by the finger size features alone. The best classification accuracy of almost 86% is generated from the little finger of the left hand. By including the ridge density, the second feature set employs all three features and its classification results are summarized in the last column of **Table 4**. It shows that the addition of the ridge density feature does not improve the effective classification accuracy. This can be explained by the poor performance of the ridge density features for gender determination.

Table 1: Summary of results for ridge counts

Finger	Male		Female		*P*-value	Classification Accuracy
	μ	σ	μ	σ		
L_2	38.32	3.11	35.57	3.30	1.14×10^{-5}	66.57
L_3	42.26	3.93	39.64	4.02	5.77×10^{-4}	59.75
L_4	41.88	2.98	39.31	3.30	2.74×10^{-5}	62.05
L_5	36.47	2.80	32.69	2.56	1.15×10^{-11}	74.95
R_2	37.67	3.21	34.38	3.16	2.02×10^{-7}	65.15
R_3	42.26	3.64	38.24	3.51	2.11×10^{-8}	68.85
R_4	41.79	3.26	38.81	3.41	5.14×10^{-6}	64.49
R_5	35.93	2.74	32.47	2.30	3.93×10^{-11}	72.00
m_L	39.73	2.63	36.80	2.88	9.49×10^{-8}	67.87
m_R	39.41	2.73	35.97	2.62	3.40×10^{-10}	72.08
m_B	39.57	2.59	36.39	2.67	2.34×10^{-9}	69.95

Table 2: Summary of results for ridge density (counts/mm)

Finger	Male		Female		*P*-value	Classification Accuracy
	μ	σ	μ	σ		
L_2	2.18	0.20	2.20	0.24	5.03×10^{-1}	46.45
L_3	2.33	0.27	2.39	0.28	2.36×10^{-1}	49.01
L_4	2.44	0.23	2.51	0.24	8.12×10^{-2}	55.36
L_5	2.37	0.24	2.41	0.25	4.91×10^{-1}	47.16
R_2	2.07	0.21	2.05	0.24	7.34×10^{-1}	47.64
R_3	2.25	0.24	2.23	0.26	6.22×10^{-1}	49.20
R_4	2.37	0.26	2.43	0.26	2.08×10^{-1}	51.25
R_5	2.31	0.21	2.33	0.23	5.71×10^{-1}	46.34
m_L	2.33	0.20	2.38	0.23	2.24×10^{-1}	50.19
m_R	2.25	0.20	2.26	0.22	7.65×10^{-1}	46.13
m_B	2.29	0.20	2.32	0.22	4.33×10^{-1}	46.81

Table 3: Summary of results for finger size (mm^2)

Finger	Male		Female		*P*-value	Classification Accuracy
	μ	σ	μ	σ		
L_2	17.66	1.18	16.20	1.02	1.35×10^{-10}	70.78
L_3	18.27	1.31	16.67	1.02	6.12×10^{-11}	74.21
L_4	17.27	1.21	15.70	1.01	1.45×10^{-11}	75.92
L_5	15.43	1.10	13.65	0.93	1.20×10^{-15}	79.01
R_2	18.28	1.24	16.82	1.17	2.34×10^{-9}	69.98
R_3	18.88	1.28	17.25	1.08	4.34×10^{-11}	73.62
R_4	17.70	1.27	16.00	0.97	1.31×10^{-12}	77.74
R_5	15.62	1.10	14.00	0.99	2.13×10^{-13}	75.91
m_L	17.16	1.16	15.55	0.94	8.32×10^{-13}	75.20
m_R	17.62	1.17	16.02	0.99	2.12×10^{-12}	75.48
m_B	17.39	1.15	15.79	0.95	8.14×10^{-13}	74.88

Table 4: Classification accuracy by using multiple features

Finger	Features employed	
	count and size[a]	**count, density and size**[b]
L_2	76.41	76.24
L_3	76.79	76.89
L_4	76.26	76.41
L_5	85.78	85.55
R_2	76.20	76.03
R_3	81.88	80.86
R_4	79.83	81.62
R_5	81.73	82.23
m_L	79.75	79.86
m_R	82.05	81.76
m_B	82.10	82.49

[a] Finger ridge and finger size index
[b] Finger ridge, finger density and finger size index

DISCUSSION AND CONCLUSION

This work proposes the use of three fingertip features for gender determination. Compared with conventional methods, the proposed approach has several distinct properties. First, since the traditional inked impressions are sensitive to factors such as skin condition, in this work finger images are captured using a digital camera. Second, compared with the conventional ridge count measure obtained by inspecting a small portion of the fingertip, the ridge count feature proposed here is obtained from a line segment that intersects the entire fingertip. Third, the possibility of using the finger size as a feature for gender differentiation is investigated. To the best of our knowledge, this has not been studied previously.

The experimental results clearly demonstrate the potential of the proposed features for gender determination. However, several issues require further study. First, among the three tested features, finger size provides the best classification accuracy. However, unlike the permanence of ridge count, finger size may change with time. Therefore, future work is needed to investigate the age effect on finger size. Second, the effectiveness of the proposed approach for different populations also requires further investigation, as gender determination may be a population specific phenomenon.[22] Third, although some previous studies have a higher finger ridge count on their right hand than on their left,[23,24] our experimental results did not support this finding. In particular, as shown in **Table 1**, for males, the mean ridge count for the left and right hands were 39.73±2.63 and 39.41±2.73 (*P*-value = 0.525), respectively. For females, the mean ridge counts for the left and right hands were 36.80±2.88 and 35.97±2.62 (*P*-value = 0.110), respectively. It is not clear whether this inconsistency is caused by the new ridge count measure employed or by the difference between the tested populations. In closing, the proposed methods look promising for gender determination. More extensive experiments are planned.

REFERENCES

1. Rao NG, Kotian MS. Foot print ratio (FPR) - a clue for establishing sex identity. *J Indian Acad Forensic Med*. 1990;2(2):51-6.
2. Robling AG, Ubelaker DH. Sex estimation from the metatarsals. *J Forensic Sci*. 1997 Nov;42(6):1062-9.
3. Işcan MY, Loth SR, King CA, et al. Sexual dimorphism in the humerus: a comparative analysis of Chinese, Japanese and Thais. *Forensic Sci Int.* 1998 Nov 30;98(1-2):17-29.
4. Mall G, Hubig M, Büttner A, et al. Sex

determination and estimation of stature from the long bones of the arm. *Forensic Sci Int.* 2001 Mar 1;117(1-2):23-30.
5. Wunderlich RE, Cavanagh PR. Gender differences in adult foot shape: implications for shoe design. *Med Sci Sports Exerc*. 2001 Apr;33(4):605-11.
6. Purkait R. Sex determination from femoral head measurements: a new approach. *Leg Med (Tokyo)*. 2003 Mar;5 Suppl 1:S347-50.
7. Ozden H, Balci Y, Demirustu C, et al. Stature and sex estimate using foot and shoe dimensions. *Forensic Sci Int.* 2005 Jan 29;147(2-3):181-4.
8. Kemkes-Grottenthaler A. Sex determination by discriminant analysis: an evaluation of the reliability of patella measurements. *Forensic Sci Int.* 2005 Jan 29;147(2-3):129-33.
9. Schwartz GT, Dean MC. Sexual dimorphism in modern human permanent teeth. *Am J Phys Anthropol.* 2005 Oct;128(2):312-7.
10. Celbis O, Agritmis H. Estimation of stature and determination of sex from radial and ulnar bone lengths in a Turkish corpse sample. *Forensic Sci Int.* 2006 May 10;158(2-3):135-9.
11. Jain AK, Hong L, Pankanti S, et al. An identity-authentication system by using fingerprints. Proc IEEE 1997;85:1365-88.
12. Holt SB. *The genetics of dermal ridges*. Springfield, Ill.: Charles Thomas; 1968.
13. Rostron J, Mittwoch U. Sex and lateral asymmetry of the finger ridge-count. *Ann Hum Biol.* 1977 Jul;4(4):375-7.
14. Mustanski BS., Bailey JM, Kaspar S. Dermatoglyphics, handedness, sex, and sexual orientation. *Arch Sex Behav.* 2002 Feb;31(1):113-22.
15. van Oel CJ, Baaré WFC, Hulshoff Pol HE, et al. Differentiating between low and high susceptibility to schizophrenia in twins: the significance of dermatoglyphic indices in relation to other determinants of brain development. *Schizophr Res.* 2001 Dec 1;52(3):181-93.
16. Saha S, Loesch D, Chant D, et al. Directional and fluctuating asymmetry in finger and a-b ridge counts in psychosis: a case-control study. *BMC Psychiatry* 2003 Mar 23;3:3.
17. Dittmar M. Finger ridge-count asymmetry and diversity in Andean Indians and interpopulation comparisons. *Am J Phys Anthropol* 1998 Mar;105(3):377-93.
18. Slabbekoorn D, van Goozen SHM, Sanders G, et al. The dermatoglyphic characteristics of transsexuals: is there evidence for an organizing effect of sex hormones. *Psychoneuroendocrinology* 2000 May;25(4):365-75.
19. Acree MA. Is there a gender difference in fingerprint ridge density? *Forensic Sci Int.* 1999 May 31;102(1):35-44.
20. Jain LC, Halici U, Hayashi I, Lee SB, Tsutsui S. *Intelligent Biometric Techniques in Fingerprint and Face Recognition.* Boca Raton: CRC Press; 1999.
21. Haykin S. *Neural network: a comprehensive foundation.* Second ed. Upper Saddle River, New Jersey: Prentice Hall; 1999.
22. İşcan MY. Forensic anthropology of sex and body size. *Forensic Sci Int.* 2005 Jan 29;147 (2-3):107-12.
23. Kimura D, Carson MW. Dermatoglyphic asymmetry: relation to sex, handedness and cognitive pattern. *Pers Individ Differ.* 1995 Oct;19(4):471–78.
24. Green R, Young R. Fingerprint asymmetry in male and female transsexuals. *Pers Individ Differ.* 2000 Nov;29(5):933-42.