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ORIGINAL ARTICLE

Gender classification from fingerprint ridge count and fingertip size using optimal score assignment

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Abstract

Information on the gender of a person plays a vital role in crime investigation, authentication and statistical report on the visitors. In this work, fingerprint ridge count and fingertip size are used as the parameters for automatic gender classification. As a novel method, the optimal score assignment (OSA) method is proposed to classify gender. An optimal score is calculated for male and female from the internally collected fingerprint database. Fingerprints are collected under four age groups and all the fingers are scanned. For the fingerprint image 'I' for which gender is to be identified, scores are assigned for ridge count and fingertip assuming that the given image is male. A similar calculation is made assuming that the given image is female. Comparing both values, gender is declared. The maximum success rate attained is 88.41% for the age group 18–25 years and a good success rate of 90.11% is achieved for the right hand ring finger. Performance evaluation is made with the earlier findings of the author and other methods.

Keywords Gender classification · Optimal score assignment · Ridge count · Fingertip size

Introduction

Ridge patterns exhibit many properties that reflect the biology of individuals. Ridge parameters such as fingerprint ridge count, ridge density, ridge thickness to valley thickness ratio, ridge width and fingerprint pattern types are used for gender determination. Variations in ridge parameters for male and female are found statistically [1, 2]. Also, it is found that dermatoglyphic features differ statistically between the sexes, ethnic groups and age categories. It is proved by various researchers that a fingerprint can be processed for sex determination [1, 3, 4].

The fingerprint samples were collected from the subjects residing in various parts of Tamil Nadu, India. The Fingkey Hamster II scanner is used for sample collection. The fingerprint image is of 8-bit gray level with a size of 300 × 260 and resolution of 500 dpi. An internal database consisting of fingerprints of 403 males and 410 females is used to test the method. All 10 fingers of each subject were scanned and thus in total, 8130 fingerprints were used. The fingerprints were categorized into four age groups, viz., 8–12, 13–18, 18–25 and above 25. For reference purpose, fingers are numbered 1–10 starting from left little finger to right little finger (left little finger 1, left thumb 5, right thumb 6 and right little finger 10).

In this manuscript, automatic gender identification from the fingerprint ridge count (RC) and fingertip size (FTS) using the OSA method is proposed. Initially, core and delta (singular points) are identified. With respect to core and delta, RCs are determined (traditional method) and in addition, ridge counts measured diagonally (at 45° and 135°) with respect to the core points are averaged. Fingertip size is measured as another parameter to find gender. A high possibility of particular values of ridge count and fingertip size for male and female is identified and given a high score. Proportionate scores are assigned to the remaining values of the ridge count and fingertip considering the most occurring ridge count and fingertip as reference. For an unknown fingerprint, different scores are assigned for RC and FTS for male and female. The sum of these two scores is calculated for male and female. If the male score (MS) is higher

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than the female score (FS), the decision is declared as male, otherwise it is declared as female. The proposed method of gender classification is demonstrated in Fig. 1.

This method of gender identification will be helpful in short listing the suspects and victims from crime scenes and improves the performance of a system which is used for person recognition and human computer interfaces.

This manuscript is organized as follows: the second section briefs the literature of various gender recognition algorithms using a fingerprint. The third section details the OSA method. In this section, singular points detection, ridge count and fingertip size measurements are elaborated. Score assignment procedure is explained and optimal score is assigned to each ridge count and fingertip size. The experimental results and performance analysis are demonstrated in the section "Experimental results". The section "Conclusion" concludes the proposed work and briefs the future work.

Related works

Although the fingerprint plays an essential role in the identification and verification, only a few machine vision methods have been proposed for gender identification. In this section, we have summarized the prior researches in gender classification.

It is demonstrated that the males have a higher ridge breadth than females [1]. Using Bayes' theorem [3] on the rolled fingerprint images belonging to the South Indian population, it is found that the fingerprint possessing ridge density < 13 ridges/25 mm^2 is most likely to be of male and ridge count > 14 ridges/25 mm^2 are most likely to be of female. Using the ridge thickness to valley thickness ratio (RTVTR) and white lines count features [4], gender was classified. According to them, the female's fingerprint is characterized by a high RTVTR, while the male's fingerprint is characterized by low RTVTR. A proposal for the interactive software system [5] that relives the tedium of visual inspection and standardizes the fingerprint ridge counting procedure is also published. In terms of age, the quality scores of 18–25 age group are good [6] compared to < 18 and > 25 age groups.

Ridge distance measurement is vital for robust performance of an automated fingerprint identification system (AFIS) irrespective of quality of the images [7]. Also, the traditional spectral analysis method was realized and a novel statistical method was presented for ridge distance estimation [8]. Ridge density in a particular space was used to classify gender using fingerprint and further demonstrated that the females have a higher ridge density compared with males. Geometric and spectral methods were used to estimate fingerprint ridge distance [9]. These methods calculate ridge direction directly. Mathematical characterization of the local frequency of sinusoidal signals and two-dimensional model was proposed [10] to approximate the ridgeline patterns for ridgeline density estimation in digital images.

Frequency domain analysis of fingerprint [11] for the identification of gender produces a good classification rate. Gender classification using fingerprints through univariate decision tree [12] was proposed and a classification rate of 96.28% was achieved. The back-propagation neural network classifier was used to classify the gender [13] and the classification rate achieved was 92.67%.

This paper demonstrates the identification of gender using the spatial parameters of the fingerprint. In this work, fingerprint ridge count and fingertip size are used as the parameters for automatic gender classification. As a novel method, the OSA method is proposed to classify gender. Information on the gender of a person plays a vital role in crime investigation, authentication and statistical report on the visitors. This method of gender identification will be helpful in short listing the suspects and victims from crime scenes and improves the performance of a system which is used for person recognition and human computer interfaces.

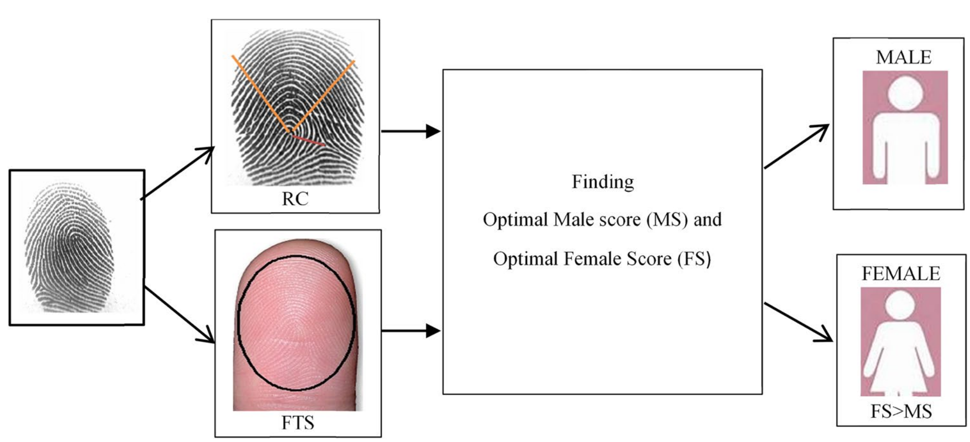

Fig. 1 Gender classification from ridge count and fingertip size

Fig. 2 Core and delta points are shown in red and blue, respectively

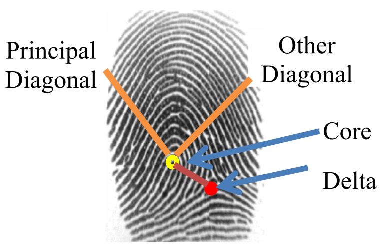

Fig. 3 Ridge count measurement

Optimal score assignment (OSA)

Singular points identification

Basically, the fingerprints are categorized as (a) tented arch, (b) left loop, (c) right loop, (d) whorl, (e) plain arch, (f) central pocket, (g) twin loops and (h) accidents. Except the plain arch [14], each type has one or more core and delta points referred to as singular points. For the plain arch, for calculation purpose, a point in a ridge which has a high peak is chosen as core and a point in the bottom-most ridge, which is almost straight, is chosen as a delta point. The types of fingerprints and its singular points are illustrated in Fig. 2.

The singular point area is defined as a region where the ridge curvature is higher than normal and where the direction of the ridge changes rapidly [15]. These singular points are useful for fingerprint indexing, i.e., for classification of fingerprint types [16], fingerprint alignment and orientation field modeling [17, 18] and identification or verification. A core point is the turning point of an innermost ridge. In biometrics and fingerprint scanning, core point refers to the central area of a fingerprint. A delta point is a place where a ridge is bifurcated (or) a delta point is a place where two ridges run side by side and diverge [19].

Ridge count

The ridge count is calculated by counting the number of ridges intervening between the delta and core [19]. In the proposed method, instead of considering counting only between the core and delta, an effort is taken to count the ridges of the entire fingertip.

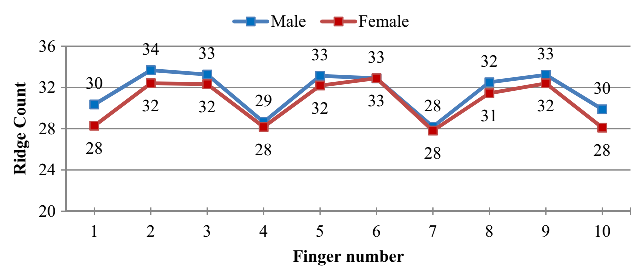

Fig. 4 Comparison of average ridge count in male and female fingerprints

Table 1 Details of finger-wise ridge count

Finger number	Ridge count					
	Minimum		Maximum		Most common RC	
	Male	Female	Male	Female	Male	Female
1	13	12	49	40	30	30
2	13	14	47	48	36	32
3	14	14	47	49	36	34
4	11	12	43	44	29	28
5	14	14	52	52	34	33
6	13	12	48	50	33	31
7	13	11	46	39	30	29
8	15	12	46	45	32	34
9	13	14	50	47	33	33
10	14	12	43	44	30	28

Table 2 RC score assigned for female and male fingers

RC	Number of occurrence		Occurrence percentage		Score assigned	
	Male	Female	Male	Female	Male	Female
12	1	7	0.0248	0.1707	0.0321	0.2439
13	6	6	0.1489	0.1463	0.1923	0.2091
14	13	11	0.3226	0.2683	0.4167	0.3833
15	14	19	0.3474	0.4634	0.4487	0.662
16	9	21	0.2233	0.5122	0.2885	0.7317
17	17	24	0.4218	0.5854	0.5449	0.8362
18	32	33	0.794	0.8049	1.0256	1.1498
19	34	44	0.8437	1.0732	1.0897	1.5331
20	49	54	1.2159	1.3171	1.5705	1.8815
21	51	78	1.2655	1.9024	1.6346	2.7178
22	66	94	1.6377	2.2927	2.1154	3.2753
23	74	104	1.8362	2.5366	2.3718	3.6237
24	91	121	2.2581	2.9512	2.9167	4.216
25	126	132	3.1266	3.2195	4.0385	4.5993
26	127	183	3.1514	4.4634	4.0705	6.3763
27	163	204	4.0447	4.9756	5.2244	7.108
28	211	263	5.2357	6.4146	6.7629	9.1638
29	236	268	5.8561	6.5366	7.5641	9.338
30	275	286	6.8238	6.9756	8.8141	9.9652
31	254	287	6.3027	7	8.1411	10
32	276	260	6.8486	6.3415	8.8462	9.0592
33	269	269	6.6749	6.561	8.6218	9.3728
34	312	263	7.7419	6.4146	10	9.1638
35	246	216	6.1042	5.2683	7.8847	7.5261
36	239	182	5.9305	4.439	7.6603	6.3415
37	195	174	4.8387	4.2439	6.25	6.0627
38	172	134	4.268	3.2683	5.5128	4.669
39	118	124	2.928	3.0244	3.7821	4.3206
40	106	58	2.6303	1.4146	3.3975	2.0209
41	67	36	1.6625	0.878	2.1474	1.2544
42	56	36	1.3896	0.878	1.7949	1.2544
43	30	24	0.7444	0.5854	0.9615	0.8362
44	14	15	0.3474	0.3659	0.4487	0.5226
45	10	13	0.2481	0.3171	0.3205	0.453
46	11	7	0.273	0.1707	0.3526	0.2439
47	3	5	0.0744	0.122	0.0962	0.1742
48	2	2	0.0496	0.0488	0.0641	0.0697
49	1	1	0.0248	0.0244	0.0321	0.0348
50	2	1	0.0496	0.0244	0.0641	0.0348
51	1	1	0.0248	0.0244	0.0321	0.0348

To enable this, an imaginary line is drawn between core and delta at 135° (referred to as the principal diagonal) and 45° (referred to as the other diagonal) as shown in Fig. 3.

Let ‘a’ be the ridge count between core to delta, ‘b’ be the ridge count in the principal diagonal and ‘c’ be the ridge count in other diagonal. The total ridge count is calculated by Eq. (1).

$$\mathrm{RC} = a + \frac{1}{2}(b + c). \tag{1}$$

Ridge counts were determined for all 8130 fingerprints of 403 male and 410 female fingerprints and analyzed. Details

Table 3 Details of finger-wise fingertip size

Finger number	Fingertip size (mm^2)					
	Minimum		Maximum		Most common fingertip size	
	Male	Female	Male	Female	Male	Female
1	225	245	535	515	460	400
2	325	279	545	530	520	455
3	340	320	545	535	515	450
4	305	265	540	535	490	455
5	380	350	545	540	530	535
6	355	270	530	540	545	530
7	290	300	540	535	485	425
8	310	260	540	535	495	495
9	230	240	510	450	505	535
10	260	215	540	520	485	400

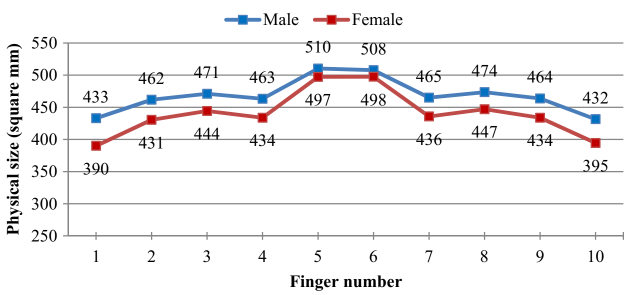

Fig. 5 Comparison of average fingertip size in male and female fingerprints

of finger-wise ridge count for male and female and the most common count are presented in Table 1.

From Table 1, it is identified that the minimum as well as the maximum RC are greater for male than female. In addition, the most common RC differs between male and female. The average RC values of male and female (for all fingerprints of the database) are compared in the line chart shown in Fig. 4.

Optimal RC score calculation

Ridge counts of all the internal database fingerprints are calculated using MATLAB. Measured fingerprint RCs are listed in an ascending order and the number of each RC is counted. The percentage of occurrence of a particular RC among total fingerprints is determined by Eq. (2) and presented in Table 2.

$$\text{Occurence percentage of RC} = \frac{\text{No. of occurence of an RC}}{\text{Total number of samples}} \times 100. \quad (2)$$

From Table 2, it is clarified that the ridge count of 31 was found to be 287 times among the 4100 female fingerprints. This is the highest occurrence in comparison with other RC counts. Its occurrence percentage is calculated as 7 and referred to as the maximum occurrence percentage. A maximum score of 10 is assigned for this RC. Scores for the remaining RC are determined by Eq. (3).

$$\text{RC score} = \frac{\text{Occurrence \% of a particular RC}}{\text{Maximum occurence \%}} \times 100. \quad (3)$$

For example, as in Table 2, RC of 25 has its occurrence percentage as 3.2195. Now, using Eq. (3), the score for RC = 25 is calculated as follows.

$$\text{RC}(=25)\ \text{score} = \frac{3.2195}{7} \times 10 = 4.5993.$$

Thus, RC scores are computed individually for male (4030 samples) and female (4100 samples) of all the internal databases and shown in Table 2.

From Table 2, it is concluded that, for female, the RC of 31 is occurring more and, for male, RC of 34 is occurring more. Here, a maximum score of 10 is assigned for each RC.

Fingertip size of the fingerprint

FTS is computed using the scanner information. The scanned image is of the size 300 × 260. In all the 8130 fingerprints of 403 males and 410 females, FTS are figured and analyzed. Comparison of FTS values is made between genders and all four age groups. The fingertip size is computed in square millimeter. The fingertip size of male and female fingerprints irrespective of the age group is analyzed and represented in Table 3.

The FTS values of male and female are compared in the line chart in Fig. 5.

Table 4 FTS score assigned for female and male fingers

FTS	Number of occurrence		Occurrence percentage		Score assigned	
	Male	Female	Male	Female	Male	Female
285	1	2	0.0248	0.0488	0.0398	0.1143
290	2	3	0.0496	0.0732	0.0797	0.1714
295	1	1	0.0248	0.0244	0.0398	0.0571
300	1	7	0.0248	0.1707	0.0398	0.4000
305	2	9	0.0496	0.2195	0.0797	0.5143
310	1	5	0.0248	0.1220	0.0398	0.2857
315	2	11	0.0496	0.2683	0.0797	0.6286
320	3	19	0.0744	0.4634	0.1195	1.0857
325	8	7	0.1985	0.1707	0.3187	0.4000
330	1	16	0.0248	0.3902	0.0398	0.9143
335	10	23	0.2481	0.561	0.3984	1.3143
340	8	16	0.1985	0.3902	0.3187	0.9143
345	9	25	0.2233	0.6098	0.3586	1.4286
350	5	32	0.1241	0.7805	0.1992	1.8286
355	11	34	0.2730	0.8293	0.4382	1.9429
360	12	35	0.2978	0.8537	0.4781	2.0000
365	7	36	0.1737	0.8780	0.2789	2.0571
370	24	41	0.5955	1.0000	0.9562	2.3429
375	17	48	0.4218	1.1707	0.6773	2.7429
380	25	66	0.6203	1.6098	0.9960	3.7714
385	30	71	0.7444	1.7317	1.1952	4.0571
390	23	54	0.5707	1.3171	0.9163	3.0857
395	36	71	0.8933	1.7317	1.4343	4.0571
400	28	118	0.6948	2.878	1.1155	6.7428
405	36	116	0.8933	2.8293	1.4343	6.6286
410	52	115	1.2903	2.8049	2.0717	6.5714
415	57	118	1.4144	2.878	2.2709	6.7428
420	50	85	1.2407	2.0732	1.9920	4.8571
425	70	132	1.7370	3.2195	2.7888	7.5428
430	71	124	1.7618	3.0244	2.8287	7.0857
435	65	148	1.6129	3.6098	2.5896	8.4571
440	76	142	1.8859	3.4634	3.0279	8.1143
445	63	106	1.5633	2.5854	2.5100	6.0571
450	88	175	2.1836	4.2683	3.5060	10.0000
455	103	174	2.5558	4.2439	4.1036	9.9428
460	129	143	3.2010	3.4878	5.1394	8.1714
465	144	148	3.5732	3.6098	5.7370	8.4571
470	119	123	2.9529	3.0000	4.7410	7.0286
475	146	160	3.6228	3.9024	5.8167	9.1428
480	158	137	3.9206	3.3415	6.2948	7.8286
485	170	133	4.2184	3.2439	6.7729	7.6000
490	175	137	4.3424	3.3415	6.9721	7.8286
495	206	120	5.1117	2.9268	8.2072	6.8571
500	113	74	2.8040	1.8049	4.5020	4.2286
505	175	106	4.3424	2.5854	6.9721	6.0571
510	191	100	4.7395	2.4390	7.6095	5.7143
515	231	90	5.7320	2.1951	9.2032	5.1428
520	234	107	5.8065	2.6098	9.3227	6.1143
525	178	79	4.4169	1.9268	7.0916	4.5143

Table 4 (continued)

FTS	Number of occurrence		Occurrence percentage		Score assigned	
	Male	Female	Male	Female	Male	Female
530	251	97	6.2283	2.3659	10.0000	5.5428
535	225	83	5.5831	2.0244	8.9641	4.7428
540	140	22	3.4739	0.5366	5.5777	1.2571
545	13	15	0.3226	0.3659	0.5179	0.8571

Optimal FTS score calculation

The fingertip size of all the internal database fingerprints is calculated using MATLAB. The measured fingerprint FTSs are listed in ascending order and the number of each FTS is counted. The percentage occurrence of a particular FTS among total fingerprints is determined by Eq. (4) and tabulated in Table 4.

$$\text{Occurence percentage of FTS} = \frac{\text{No. of occurence of an FTS}}{\text{Total number of samples}} \times 100. \quad (4)$$

From Table 4, it is clarified that the fingertip size of 450 mm^2 was found 175 times among the 4100 female fingerprints. This is the highest occurrence in comparison with other FTS counts. Its occurrence percentage is calculated as 4.2683 and referred to as the maximum occurrence percentage. A maximum score of 10 is assigned for this FTS. Scores for the remaining FTS are determined by Eq. (5).

$$\text{FTS score} = \frac{\text{Occurrence \% of a particular FTS}}{\text{Maximum occurence \%}} \times 100. \quad (5)$$

For example, as in Table 4, FTS = 400 has its occurrence percentage as 2.8780. Now, the score is calculated as follows.

$$\text{FTS } (= 400) \text{ Score} = \frac{2.8780}{4.2683} \times 10 = 6.742.$$

Thus, FTS scores are computed individually for male (4030 samples) and female (4100 samples) of all the internal databases and shown in Table 4.

From Table 4, it is concluded that the FTS of 450 mm^2 and 530 mm^2 are occurring more for female and male, respectively.

Experimental results

A detailed analysis of RC and FTS was carried out in the previous section. From the analysis, it is observed that the ridge count and the fingertip size of the fingerprints are more for male than female. Also, all these values differ for male and female in all the age groups. The novel method of OSA is discussed and the scores are assigned in this section. As the scores assigned for a particular value of RC/FTS are different for male and female, the sum of these scores computed for each gender is distinguishable and thus declares more accurate results.

Let I be the fingerprint image for which the gender needs to be identified. Considering I as the male fingerprint, the total score I_{MS} is calculated by Eq. (6).

$$I_{MS} = RC_M + FTS_M, \quad (6)$$

where RC_M and FTS_M are the respective scores of ridge count and fingertip size assigned for male fingerprints. Similarly, considering I as a female fingerprint, the total score of I_{FS} is calculated by Eq. (7).

$$I_{FS} = RC_F + FTS_F \quad (7)$$

where RC_F and FTS_F are the respective scores of ridge count and fingertip size assigned for female fingerprints. The gender of the unknown fingerprint I is declared as male if $I_{MS} > I_{FS}$, and otherwise declared as female. Two examples are shown in the Table 5.

Age group-wise gender classification

Age group-wise gender classifications are presented in Table 5. The number of samples used is 44, 55, 198 and 106 for each finger in the age groups 8–12, 13–18, 19–25 and > 25, respectively. Thus, collectively 4030 samples were used for testing the proposed method. For the age group 19–25 years, the results are good and the success rate achieved is 88.41%. The success rate for the right hand ring fingers in this group achieved is 90.11%.

Performance evaluation

In this section, a novel approach of the gender classification using the OSA method is compared with various methods experimented by the author [12, 20, 21]. The best results were

Table 5 Age group-wise success rate (in %) for male samples by OSA method

Finger number	Male	Female	Overall
Age group 8–12 years			
Success rate (%)			
1	82.61	90.00	86.31
2	84.39	87.42	85.91
3	88.93	87.42	88.18
4	91.70	83.75	87.73
5	91.70	83.76	87.73
6	91.70	81.67	86.69
7	88.93	83.33	86.13
8	84.89	83.38	84.14
9	82.61	87.46	85.04
10	79.84	90.2	85.02
		Average	86.28
Age group 13–18 years			
Success rate (%)			
1	84.84	89.76	87.30
2	87.16	87.96	87.56
3	88.48	87.16	87.82
4	90.30	82.76	86.53
5	90.53	80.67	85.60
6	85.46	81.96	83.71
7	88.56	84.56	86.56
8	84.92	82.94	83.93
9	87.32	87.16	87.24
10	83.52	83.27	83.39
		Average	85.96
Age group 19–25 years			
Success rate (%)			
1	86.66	90.55	88.61
2	89.68	89.51	89.60
3	91.2	87.96	89.58
4	92.21	84.87	88.54
5	91.71	83.83	87.77
6	92.17	83.72	87.95
7	90.69	83.31	87.00
8	90.53	82.81	86.67
9	91.21	89.00	90.11
10	89.18	87.46	88.32
		Average	88.41
Age group > 25 years			
Success rate (%)			
1	85.37	88.64	87.01
2	86.32	87.55	86.94
3	89.15	84.88	87.02
4	90.59	83.21	86.90
5	89.65	82.12	85.89
6	88.71	80.52	84.62
7	90.59	83.79	87.19
8	87.26	85.97	86.62
9	89.56	87.55	88.56
10	85.37	89.73	87.55
		Average	86.83

obtained for the age group 19–25 years alone compared with the earlier publications of the author in Table 6.

From the results shown in Table 7, it is observed that the OSA method results (age group 19–25 years) are good individually for male and female. As an overall result, the classification rate achieved is 88.41%. Figure 6 illustrates the increase in classification rate (%) from the frequency domain technique to the spatial parameters technique.

Badawi et al. [4] compared RTVTR, ridge count, white lines count, ridge count asymmetry and pattern type concordance as features. FCM, LDA, and NN classifiers were used for gender classification. For this study, the RTVTR, and white lines count features were analyzed for 255 persons (150 males, and 105 females). Table 7 shows only the overall classification rate obtained by Badawi et al. [4], and the proposed method (age group of 19–25). Verma and Agarwal [22] used ridge density and ridge width in addition to RTVTR as features and with the SVM classifier, the results obtained by them are shown in Table 7. They used a dataset of 400 fingerprints (200 males and 200 females) of Indian origin in the age group of 18–60 years. These fingerprints were divided equally for training and testing with SVM classifier.

Conclusion

A novel method of OSA technique was proposed for gender classification using the ridge count and fingertip size. Performance evaluation was done with the methods tested and the earlier methods by other researchers.

For the proposed method, the spatial parameters, ridge count and fingertip size, and the OSA method were used for gender classification. An extensive analysis of both parameters was done and it is found that all the values obtained are greater for male than female. An algorithm for assigning score for each value of the parameters was discussed. This method produced a success rate of 88.41% and 90.11% is achieved for the right hand ring finger. A comparative performance evaluation was carried out with the other methods tested by the present researchers. Thus, the proposed method achieves better results than all the methods discussed. Also, the OSA method works well even for the poor quality fingerprints. To improve the success rate further, other fingerprint features can also be included.

Table 6 Performance comparison (in %) of the proposed method

Features used	FFT, DCT & PSD	DWT level 6	SVD	DWT level 6 & SVD	RC &FTS
Classifiers	Threshold	KNN	KNN	KNN	OSA method
Male	85.15	88.89	90.34	89.24	90.52
Female	83.80	84.35	85.32	87.15	86.30
Overall	84.51	86.62	87.83	88.20	88.41

Table 7 Performance comparison with the existing methods

	Badawi et al. [4]			Verma and Agarwal [22]	Proposed method
Features used	RTVTR, white line count, ridge count asymmetry pattern type			RTVTR, ridge width and ridge density	Ridge count, and fingertip size
Classifiers	FCM	LDA	NN	SVM	OSA method
Male	58.67	96.15	90.38	86	90.52
Female	56.33	72.97	83.78	90	86.30
	56.47	86.52	87.64	88	88.41

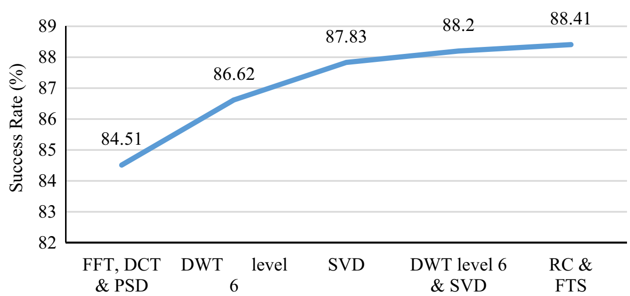

Fig. 6 Comparison of overall classification rate of all the methods developed

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