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Fingerprint Recognition using Texture Features

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Abstract: ***This paper proposes an efficient scheme of fingerprint recognition for biometric identification of individuals. Three statistical features are extracted from fingerprint images and represented using a mathematical model. These features are (1) an entropy coefficient, computed from the intensity histogram of the image, (2) a correlation coefficient, computed by correlation operation between the original image and a filtered version of the image obtained using a 2D median filter, and (3) an energy coefficient, obtained by first subjecting the image to a 5-level wavelet decomposition and thereafter computing the percentage energy of the approximation coefficient obtained after the 5th level decomposition. The approach is tested over a dataset of 80 images divided into 10 classes and is seen to provide accurate recognition results.***

Keywords: Fingerprint recognition, entropy, correlation, wavelet energy

1. Introduction

Biometrics refers to a set of techniques used to identify individuals based on their physiological characteristics. Such characteristics include retinal patterns, iris patterns, fingerprint, palm print, facial features, voice patterns etc. Digital image or audio capturing such traits are submitted to image processing and pattern recognition techniques to extract computer recognizable features which are used to match them previously stored such information and hence identify or authenticate the persons concerned. Fingerprint recognition has advantages in that the images can be acquired relatively easily, quickly and using low cost equipment and the matching process can also be done efficiently as the images are of small dimensions. Also each person is assumed to have a unique fingerprint pattern due to which the process can have good accuracy and hence is even used at commercial places. Challenges in fingerprint recognition include building a reliable data model to represent randomly oriented lines of the finger tip and finding ways to comparing the models with accuracy and in real time. Added to these there can be other difficulties like rotational or lighting variations or even noises generated from acquisition devices. This paper presents an efficient algorithm for fingerprint recognition by considering various statistical features from fingerprint images. The organization of the paper is as follows : section 2 provides an overview of related works, section 3 outlines the proposed approach, section 4 provides details of the experimentations done and the results obtained, and section 5 brings up the overall conclusions and future scopes.

2. Related Works

A number of techniques have been proposed for fingerprint recognition in extant literature. Gray Level Co-occurrence Matrix GLCM along with k-NN classifier have been used in [1], a correlation based approach for low-quality images have been proposed in [2], while a minutiae based model representing ridge ending and ridge bifurcation have been proposed in [3]. To reduce dimensions of the feature space, a Fingerprint Expression Tensor has been proposed as a multi-linear generalization of Independent Component Analysis [4]. A method based on pseudo-singularity points has been proposed to improve recognition when the standard singularity points of minutiae cannot be extracted [5]. A combination of Fourier Transform and Gabor Filters has been proposed in [6] while Discrete Wavelet Transform have been used in [7] to identify features in low quality images. Methods based on identifying the focal point of curved ridges of minutiae and their matching using polar coordinates have been proposed in [8]. Artificial Neural Networks have been used to classify minutiae into 8 classes in [9]. Coefficients generated from various wavelets viz. Haar, Daubechies and Symmlet, along with a k-NN classifier have been proposed in [10]. In [11] a set of 52 bifurcation patterns and Euclidean distance metric is used for fingerprint recognition.

3. Proposed Approach

The proposed approach utilizes three texture based features for recognizing fingerprint classes viz entropy, 2D correlation coefficient and energy of wavelet coefficients. Each of these three features are represented as scalar values and the combined feature vector is therefore a 3-element vector.

3.1 Entropy

Entropy is a statistical measure of randomness that can be used to characterize the texture of an image. It is defined in equation (1) below, where P_i is the i th frequency value generated from a k-bin normalized intensity histogram of the image.

$$E_n = -\sum_{i=1}^{k} P_i log_2 P_i \qquad (1)$$

The normalized values are computed by dividing each frequency count by sum of pixels in the image, as given in equation (2) where f_i is the i-th frequency value of the histogram and N the total number of pixels.

$$P_i = \frac{f_i}{N} \qquad (2)$$

3.2 Correlation

The image is first subjected to a 2-D median filter using a 3 × 3 neighborhood. The correlation coefficient is computed using equation (3), where I_{mn} is the original image of dimensions $m \times n$ and J_{mn} is the filtered version of the same, and $\bar{I}$ and $\bar{J}$ denote the mean pixel values of the corresponding images.

$$C_c = \frac{A}{B}, where$$

$$A = \sum_m \sum_n (I_{mn} - \bar{I})(J_{mn} - \bar{J}) \quad (3)$$

$$B = \sqrt{\left\{\sum_m \sum_n (I_{mn} - \bar{I})^2\right\}\left\{\sum_m \sum_n (J_{mn} - \bar{J})^2\right\}}$$

3.3 Energy

For calculating the energy coefficient, the image I is subjected to a wavelet decomposition using the Daubechies wavelet for up to 5 levels. The wavelet decomposition involves convolving the image with a low-pass filter for generating the approximation coefficients (A) and a high-pass filter for generating the detail coefficients (D), followed by a down-sampling. The data image for each level is taken as the approximation image for the previous level. The decomposition operation generates the approximation coefficients A_5 and detailed coefficients D_5, D_4, D_3, D_2, D_1, as shown in Fig. 1 below.

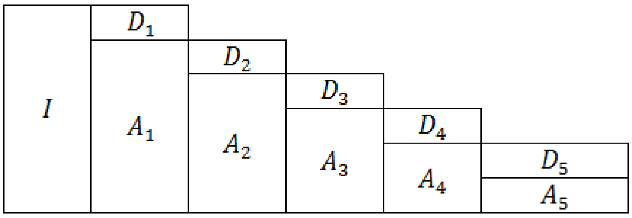


Figure 1: Wavelet decomposition of an image I

The percentage of the energy corresponding to the approximation coefficient is subsequently computed as given below;

$$E_a = \sum(A_5) / \sum(A_5 + D_5 + D_4 + D_3 + D_2 + D_1) \quad (4)$$

The final feature vector is taken as the composite formed of the above three components viz.

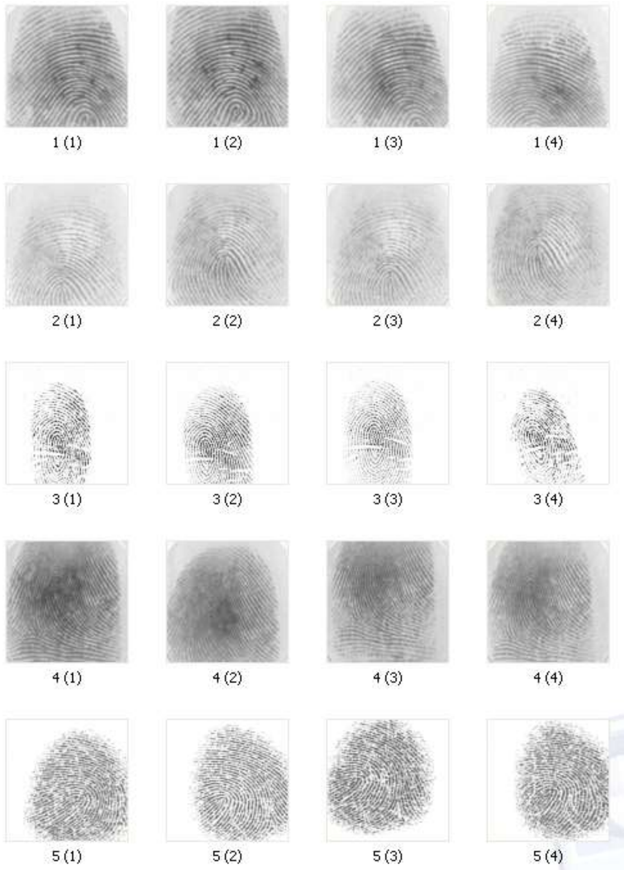
$$F = \{C_c, \quad E_n, \quad E_a\} \quad (5)$$

Classification is done by mapping the feature vectors of a training set and a testing set into appropriate feature spaces and calculating differences using Manhattan distance. The Manhattan distance metric (d) of two n-dimensional vectors $T = \{T_1, T_2, \ldots, T_n\}$ and $S = \{S_1, S_2, \ldots, S_n\}$ is given by

$$d = \sum_{i=1}^{n} |T_i - S_i| \quad (6)$$

4. Experimentations and Results

To test the efficacy of the proposed method experimentations were performed taking images from FVC2000 database [12]. The dataset consists of 80 images divided into 10 classes with 8 images per class. 4 images per class are used for training the system while the remaining four are used for testing. Samples of the images are shown in Fig. 2 and 3. The caption nomenclature is *class (sample)*. The images have standard dimensions of 300 × 300 and stored in TIF format.



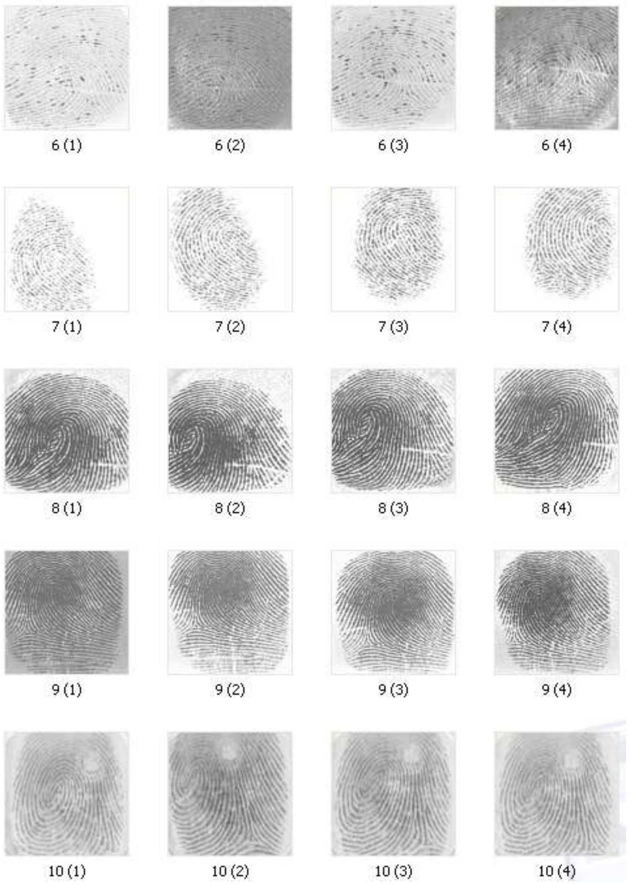
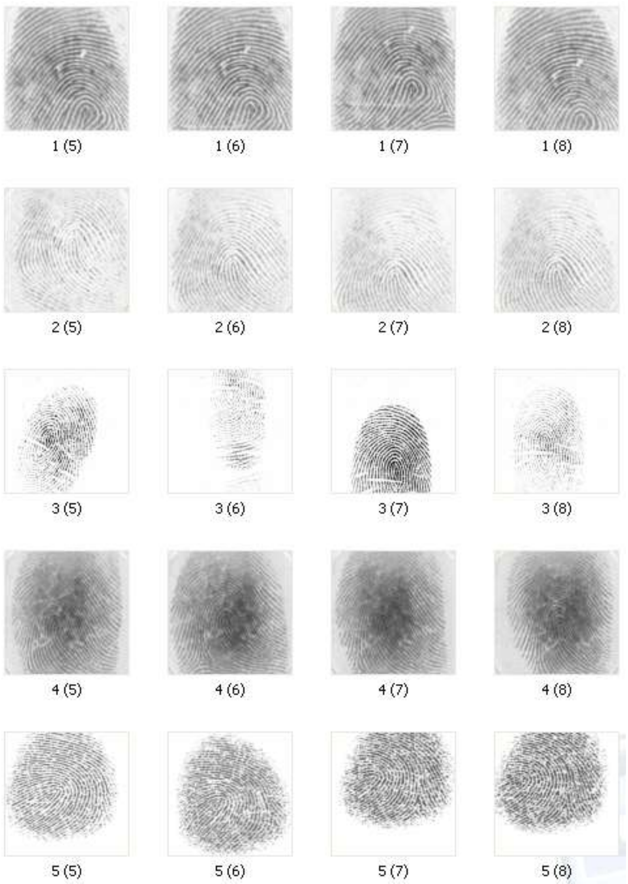


Figure 2: Samples of the training set



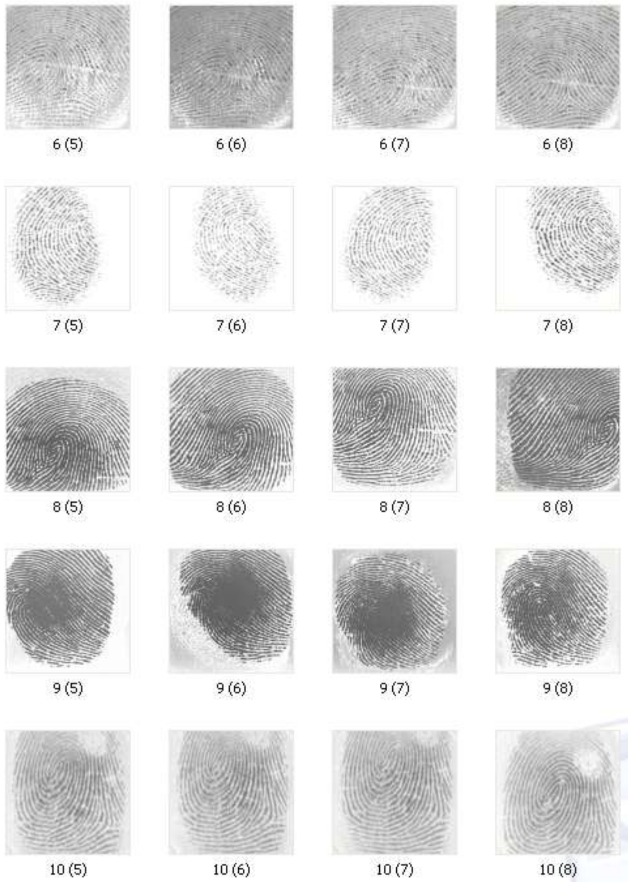


Figure 3: Samples of the testing set

As part of the training phase, 4 images of each class are read sequentially and their feature vectors are computed according to relations mentioned previously. Feature values for the first three classes are mentioned in Table 1 below.

Table 1: Sample feature values for Training set images (T)

Class	*Sample no.*	C_c	E_n	E_a
1	1	0.9954	7.0154	98.9342
	2	0.9949	7.0448	98.5771
	3	0.9963	6.9760	99.2170
	4	0.9957	6.7537	99.4345
2	1	0.9870	5.9009	99.7514
	2	0.9904	6.3009	99.6103
	3	0.9870	6.0258	99.7647
	4	0.9885	6.1893	99.6701
3	1	0.9669	2.7170	97.9415
	2	0.9695	3.1986	97.6939
	3	0.9525	2.9878	98.4556
	4	0.9655	2.5369	98.3412

The variation of the feature values for all ten classes is shown in Fig. 4 by considering the average values of the samples for each class. The corresponding class average values are mentioned in Table 3.

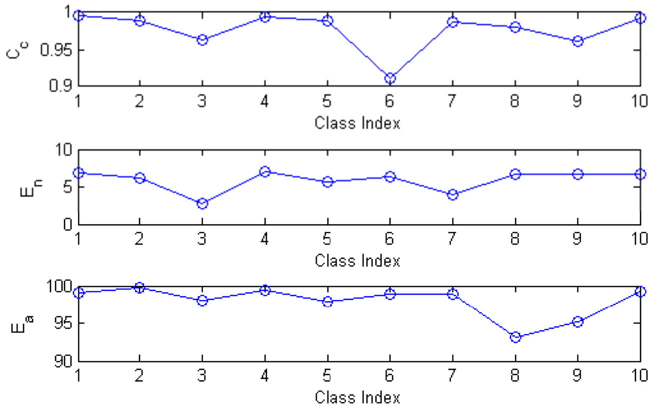


Figure 4: Variation of feature values for Training set

Likewise for the testing phase, the remaining 4 images of each class are read sequentially and their feature vectors are computed. Feature values for the first three classes are mentioned in Table 2.

Table 2: Sample feature values for Testing set images (S)

Class	*Sample no.*	C_c	E_n	E_a
1	5	0.9945	6.9943	98.7030
	6	0.9936	6.9219	98.5084
	7	0.9929	6.9100	98.5595
	8	0.9941	6.8909	98.8262
2	5	0.9835	5.6778	99.6908
	6	0.9882	5.9193	99.6379
	7	0.9875	5.7069	99.7221
	8	0.9893	5.8907	99.6680
3	5	0.9668	3.0992	98.3573
	6	0.9463	2.1536	99.4582
	7	0.9844	3.5199	96.1976
	8	0.9464	2.6324	99.2349

The variation of the feature values for all ten classes is shown in Fig. 5 by considering the average values of the samples for each class. The corresponding class average values are mentioned in Table 4.

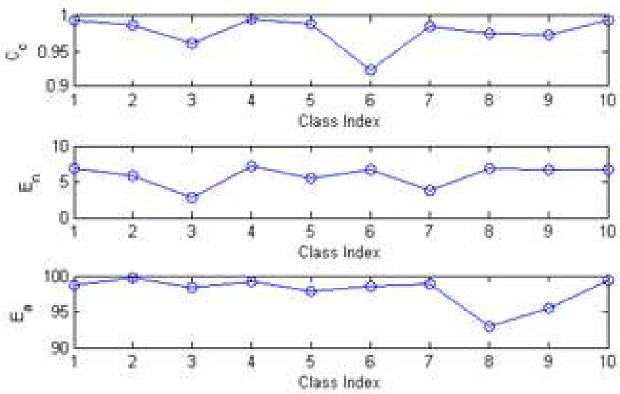


Figure 5: Variation of feature values for Testing set

Table 3: Class average feature values for Training set (μT)

C_c	0.9956	0.9882	0.9636	0.9944	0.9885
	0.9118	0.9869	0.9794	0.9618	0.9923
E_n	6.9475	6.1042	2.8601	6.9759	5.6031
	6.3556	4.0116	6.6868	6.7344	6.6216
E_a	99.0407	99.6991	98.1080	99.3248	97.8387
	98.8267	98.8458	93.1135	95.2443	99.2779

Table 4: Class average feature values for Testing set (μS)

C_c	0.9938	0.9871	0.9610	0.9961	0.9889
	0.9231	0.9861	0.9742	0.9737	0.9936
E_n	6.9293	5.7987	2.8513	7.1660	5.5409
	6.7175	3.8971	6.9126	6.6750	6.6921
E_a	98.6493	99.6797	98.3120	99.3040	97.8179
	98.5423	98.9605	92.9002	95.4689	99.3344

Classification is done by subtracting feature values of each test sample from the mean training set values given in Table 3 and considering absolute values of the difference components (Manhattan distance). For each test sample 10 difference vectors are generated corresponding to 10 classes. The mean value of each of these 10 difference vectors is used for classification. The test sample is considered to be a member of that class for which the mean difference value is minimum. The process is illustrated for the first test sample 1(5) given in Table 2 i.e. S_1 = [0.9945, 6.9943, 98.7030]. The mean training vector of class 1 as in Table 3 is μT_1 = [0.9956, 6.9475, 99.0407]. The absolute difference is then: $d_{11} = |S_1 - \mu T_1|$ = [0.0011, 0.0468, 0.3377]

The mean difference value is μd_{11} = 0.1285. Similarly difference values with other 9 classes are computed viz. $[\mu d_{11}, \mu d_{12}, \mu d_{13}, \ldots]$ = [0.1285, 0.6308, 1.5867, 0.2134, 0.7538, 0.2817, 1.0444, 1.9707, 1.2505, 0.3166]. Since the minimum value of 0.1285 corresponds to class 1, sample S_1 is classified as belonging to class 1. Fig. 6 below shows the difference plots of test samples 1(5), 2(5), 3(5) which indicates that the difference with classes 1, 2, 3 are minimum respectively.

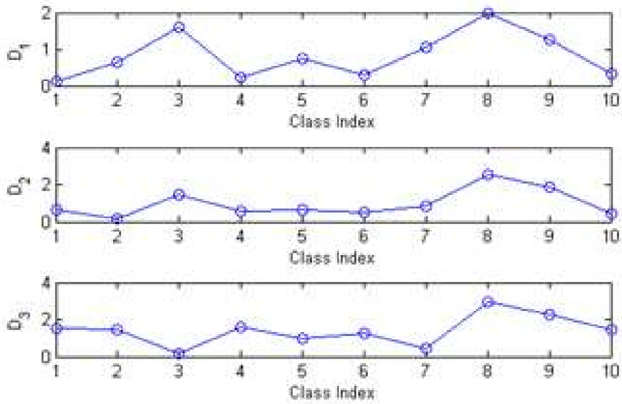


Figure 6: Difference plots for 3 test samples

Table 5 below indicates the mean difference value between each test sample and all the 10 training classes.

Table 5: Difference values for Testing set (μd)

Test sample	*Mean Difference with 10 classes*
1 (5)	0.1285 0.6308 1.5867 0.2134 0.7538 0.2817 1.0444 1.9707 1.2505 0.3166
1 (6)	0.1866 0.6713 1.4974 0.2904 0.6645 0.3222 1.0848 1.8814 1.1612 0.3570
1 (7)	0.1738 0.6500 1.5102 0.2776 0.6773 0.3009 1.0636 1.8942 1.1740 0.3358
1 (8)	0.0908 0.5552 1.5932 0.1946 0.7603 0.2061 0.9688 1.9772 1.2570 0.2409
2 (5)	0.6439 0.1465 1.4735 0.5583 0.6439 0.5379 0.8381 2.5301 1.8416 0.4552
2 (6)	0.5442 0.0821 1.5379 0.4586 0.7052 0.4413

	0.9004 2.4335 1.7450 0.3555
2 (7)	0.6433 0.1403 1.4949 0.5577 0.6627 0.5399 0.8574 2.5322 1.8437 0.4546
2 (8)	0.5634 0.0819 1.5388 0.4778 0.7059 0.4612 0.9012 2.4535 1.7650 0.3747
3 (5)	1.5201 1.4561 0.1639 1.6239 1.0147 1.2603 0.4736 2.9479 2.2511 1.4895
3 (6)	1.7535 1.4111 0.6913 1.6679 1.7037 1.6226 0.8370 3.6370 2.9367 1.5648
3 (7)	2.0939 2.0299 0.8637 2.1977 1.2428 1.8458 1.0474 2.0853 1.3968 2.0633
3 (8)	1.5195 1.3260 0.4572 1.4938 1.4696 1.3886 0.6029 3.4029 2.7026 1.3594
4 (5)	0.1434 0.4579 1.8274 0.0405 0.9945 0.4400 1.1899 2.2114 1.4912 0.1740
4 (6)	0.1547 0.5318 1.8387 0.1144 1.0058 0.4513 1.2012 2.2227 1.5025 0.2176
4 (7)	0.1906 0.4976 1.8746 0.0868 1.0417 0.4872 1.2371 2.2586 1.5384 0.2212
4 (8)	0.1545 0.4658 1.8385 0.0507 1.0057 0.4511 1.2010 2.2225 1.5023 0.1852
5 (5)	0.9587 0.8947 0.8471 1.0625 0.1653 0.7132 0.7015 2.1045 1.4160 0.9281
5 (6)	0.5908 0.5274 1.0932 0.6946 0.2603 0.3458 0.8237 1.9828 1.2942 0.5602
5 (7)	0.9556 0.8923 1.0094 1.0594 0.1051 0.7108 0.8638 1.9429 1.2544 0.9250
5 (8)	1.0095 0.9459 1.1690 1.1133 0.1587 0.7644 1.0233 1.7831 1.0945 0.9789
6 (5)	0.2056 0.5664 1.5015 0.3094 0.6853 0.1778 0.9791 1.8960 1.1641 0.2549
6 (6)	0.3059 0.6290 1.4169 0.4097 0.6007 0.2289 1.0416 1.8127 1.1125 0.3174
6 (7)	0.2238 0.5468 1.4876 0.3276 0.6714 0.1539 0.9595 1.8835 1.1832 0.2353
6 (8)	0.3325 0.7049 1.3702 0.4363 0.5540 0.3206 1.1175 1.7647 1.0327 0.3933
7 (5)	0.9579 0.8938 0.7261 1.0617 0.8107 0.7572 0.0886 2.7495 2.0609 0.9273
7 (6)	1.3234 0.9790 0.6410 1.2378 1.2736 1.2164 0.4068 3.2086 2.5201 1.1347
7 (7)	1.0614 0.9016 0.7183 1.0695 1.0116 0.9575 0.1449 2.9497 2.2612 0.9350
7 (8)	1.2202 1.1562 0.4638 1.3240 0.6776 0.9745 0.1892 2.6167 1.9282 1.1896
8 (5)	2.0709 2.5690 3.1215 2.1558 2.1160 2.2132 2.9817 0.1767 0.8761 2.2575
8 (6)	2.1688 2.6425 3.1941 2.2726 2.1895 2.2858 3.0552 0.2502 0.9487 2.3310
8 (7)	2.0189 2.3200 2.8724 2.1227 1.8670 1.9641 2.7326 0.0732 0.6820 2.0084
8 (8)	2.1322 2.6303 3.1733 2.2170 2.1773 2.2650 3.0429 0.2379 0.9279 2.3187
9 (5)	1.4382 1.3741 1.8673 1.5420 0.8596 1.1881 1.7253 1.0797 0.3912 1.4076
9 (6)	1.2414 1.7395 2.2894 1.3413 1.2865 1.3811 2.1522 0.8339 0.1102 1.4280
9 (7)	1.0946 1.5927 2.1377 1.1794 1.1397 1.2294 2.0054 1.0816 0.3531 1.2812
9 (8)	1.4845 1.7759 2.3244 1.5883 1.3229 1.4161 2.1886 0.6212 0.1437 1.4644
10 (5)	0.1453 0.3577 1.6749 0.1129 0.8420 0.2874 1.0373 2.0589 1.3498 0.0434
10 (6)	0.1752 0.3278 1.6966 0.0913 0.8637 0.3091 1.0590 2.0806 1.3794 0.0432
10 (7)	0.1736 0.3294 1.6867 0.1011 0.8538 0.2992 1.0492 2.0707 1.3776 0.0333
10 (8)	0.2406 0.2624 1.7263 0.1550 0.8934 0.3388 1.0887 2.1340 1.4455 0.0729

The minimum difference values for each of the samples are highlighted by shading. As the entire test samples are observed to be correctly classified, recognition accuracy is 100%.

5. Conclusions and Future Scope

This paper has proposed a quick and efficient technique of fingerprint recognition using a set of texture based features. The features are derived from a correlation coefficient, an entropy coefficient and an energy coefficient. The features can be calculated quickly leading to a quick recognition response. Moreover such texture based techniques can prove to be more useful than standard minutiae based approaches when the fingerprint images are captured using low lighting and / or noisy environments where minutiae details cannot be extracted reliably. Future work would involve combining color and shape based techniques to study whether these can be used to improve recognition rates.

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