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Fingerprint Detection Using Canny Filter and DWT, a New Approach

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Abstract—This paper proposes two new methods to detect the fingerprints of different persons based on one-dimensional and two-dimensional discrete wavelet transformations (DWTs). Recent literature shows that fingerprint detection based on DWT requires less memory space compared to pattern recognition and moment-based image recognition techniques. In this study four statistical parameters - cross correlation co-efficient, skewness, kurtosis and convolution of the approximate coefficient of one-dimensional DWTs are used to evaluate the two methods involving fingerprints of the same person and those of different persons. Within the contexts of all statistical parameters in detection of fingerprints, our second method shows better results than that of the first method.

Keywords—Canny Filter, Color Inversion, Skewness, Kurtosis and Convolution

1. Introduction

Discrete wavelet transformation (DWT) transforms a continuous time signal $f(t)$ but the discretization is done only in a and b (a for wavelet dilation and b for translation respectively) and is widely used for image processing [1, 2]. Usually a one-dimensional wavelet transform is used in decomposition and synthesis of voice or data signals, but for image analysis a two-dimensional wavelet transform is used, which is much more complicated than the one-dimensional case. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal (shown in Appendix-A).

When a signal is simultaneously passed through a low pass and high pass filter, the output of the low pass filter containing the low frequency content of the signal is called an approximation, which gives the signal identity. The output of the high pass signal on the other hand, is called the details, and provides the tone of the signal as summarized in [3, 4]. For digital sequencing the number of samples at the output of both low pass and high pass filter is equal to the number of samples of the original message.

The Fingerprint technique is one of the most reliable biometric technologies as fingerprints preserve universality, uniqueness, permanence, and collectability characteristics for personal identification. Several approaches of fingerprint matching have been proposed in recent literature. One approach is taking the 9^{th} level DWT of the original fingerprint image; from which

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three linear lines can be obtained. The slopes of these lines are then stored as numerical values in a matrix form, which are then used as the template values for the fingerprint image. Fingerprint recognition is performed by comparing the slope values of the input image with the stored template values. This method yields about a 95% recognition rate as explained in [5].

An image based automatic fingerprint matching approach is proposed in [6]. The fingerprint images are matched based on the features extracted in the wavelet domain. The feature vector represents an approximation of the image energy distribution over different scales and orientation. Using this method, about a 95.2% recognition rate is achieved.

A hierarchical fingerprint matching system is proposed in [7] that utilized features at three levels- Level 1 (pattern), Level 2 (minutia points) and Level 3 (pores and ridge contours), extracted from high resolution (1,000 ppi) fingerprint scans. Here Gabor filters and wavelet transform are used to automatically extract the Level 3 features and are locally matched using an Iterative Closest Point (ICP) algorithm. This approach focuses on the Level 3 features of the fingerprint as it carries significant discriminatory information and also shows that by employing Level 3 features, a 20% equal error rate (EQR) has been reduced. A combination of features for multi-scale and multi-directional recognition of fingerprints is proposed in [8]. The features include standard deviation, kurtosis, and skewness. This method is applied by analyzing the fingerprints using discrete wavelet transform (DWT). However, this method does not incorporate any image filter to sharpen the pixels.

The present paper uses the Canberra distance metric to determine the similarity between the texture classes. The proposed algorithm can detect fingerprints even if they are at some other orientation. Also the approach is very simple compared to the minutia point pattern matching algorithm. Above a 95% recognition rate is achieved using this method. The Canny filter is an edge detection technique based on the first derivative of a Gaussian function, because it is susceptible to the noise present on raw unprocessed image data, so to begin with, the raw image is convolved with a Gaussian filter. The result is a slightly blurred version of the original, which is not affected by a single noisy pixel to any significant degree.

The rest of this paper is organized as follows. Sec. II deals with the methodology of the proposed model, Sec. III reveals the results of the paper and finally Sec. IV concludes the entire analysis.

2. Methodology

In this paper we proposed two different methods to detect fingerprints of different persons based on DWT.

2.1 Method 1

Several fingerprints of a person are taken in a random manner (in context of translation and rotation) followed by a two-dimensional DWT. Four filtered signals (level-one (approximation), level-two (horizontal details), level-three (vertical details), and level-four (diagonal details)) A, B, C and D are again transformed at 9 levels DWT and the approximations are stored instead of the original images. The transformed signal matrices $\mathbf{T_{i,n}} = [A_{i,n}\ B_{i,n}\ C_{i,n}\ D_{i,n}]^T$; where $n = 1, 2, 3, \ldots, M$, and M is the number of stored matrices of user i. To recognize the fingerprint of a person, his image is scanned and the same job is done to determine the matrix $\mathbf{T_{i,n}}$. Finally, a convolution is made with stored vectors y_i of $\mathbf{T_{i,n}}$ and the corresponding vectors of the present scanned image and corresponding convolution vectors v_i are stored. Finally skewness, kurtosis and cross correlation co-efficient of normalized y_i is taken for both cases (fingerprint of same person and different person). The mathematical equations regarding different models mentioned in this section is given in Appendix-A.

2.2 Method 2

In this method, several fingerprints of a person are taken in a random manner as in the previous method (in context of translation and rotation) then an RGB conversion is performed on them. The contrast of the images is increased using a Canny filter then color inversion is performed on them. Then the same process, as in method 1 is executed. The entire process is shown in the flowchart, as in Fig. 1.

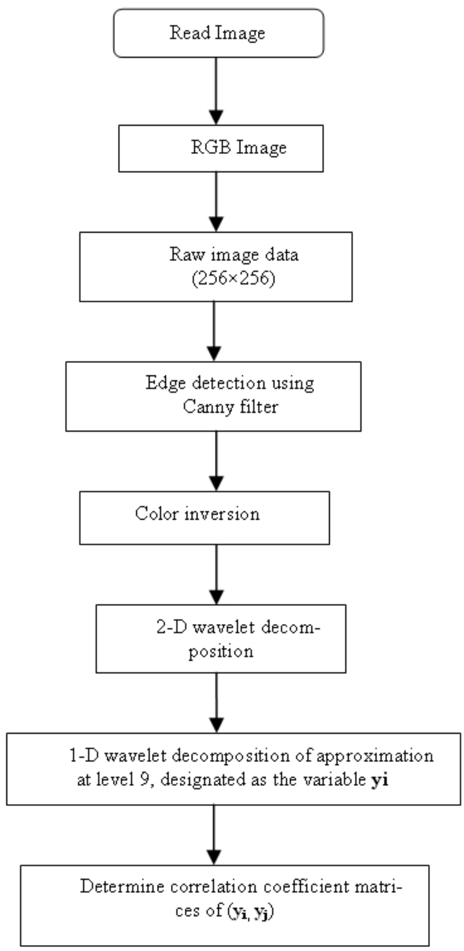


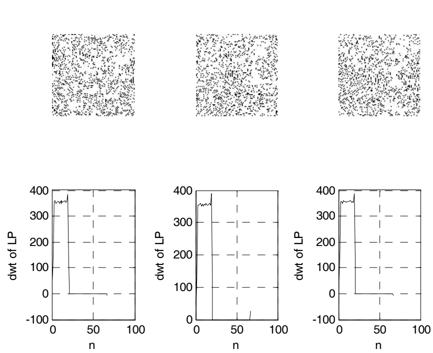
Fig. 1. Flowchart of image processing

3. RESULTS

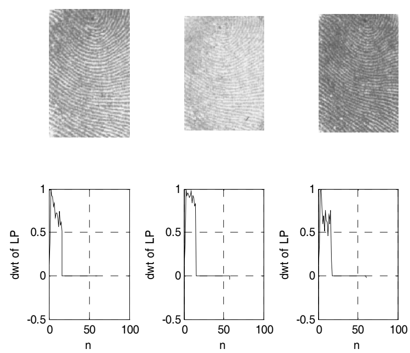
To begin with, three fingerprints of the same person are taken in a random manner (in context of rotation and translation) and their 9th levels 1-D DWT of approximation **A** is shown in Fig. 2. Fig. 2(a) is a Method 1case, and Fig. 2(b) is a Method 2 case which follows the flowchart of Fig. 1. The vectors correspond to approximation **A** of the three images which are designated as y_1, y_2 and y_3. All the curves seem to be very close but Method 2 provides the better result.

The convolutions are between (y_1, y_2), (y_2, y_3) and (y_3, y_1) are v_1, v_2 and v_3 respectively and are plotted in Fig. 3, after normalization where three curves merge very closely. In this case, both methods show almost the same performance.

Three finger prints of different persons are taken in a random manner. The approximate part **A** of 2D-DWT of each image is selected, and 9th level 1D-DWT is taken on each approximate vector **A** from each image. The resulting vectors are shown in Fig. 4. The results and corre-

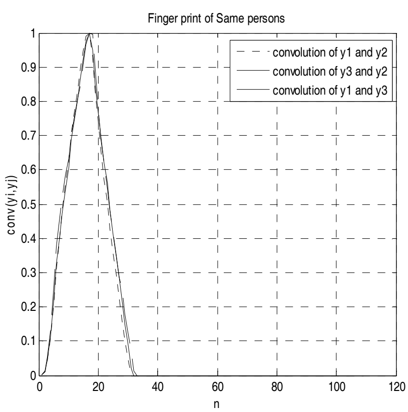


(a) Method 1

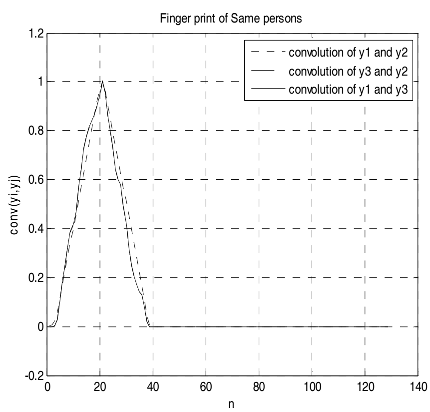


(b) Method 2

Fig. 2. Fingerprints and corresponding 9th level approximations of A for the same person

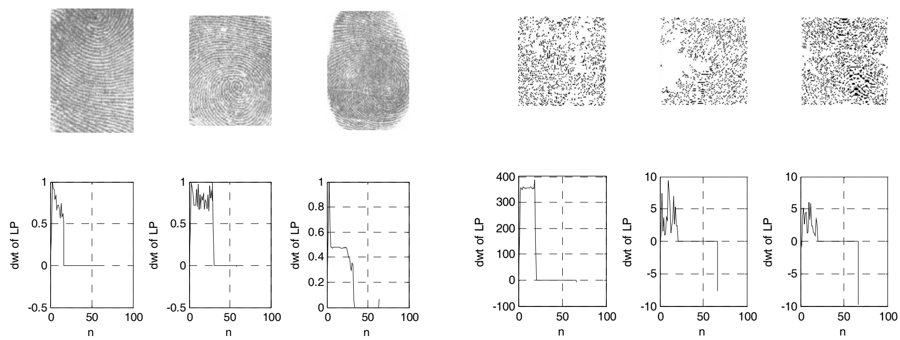


(a) Method 1



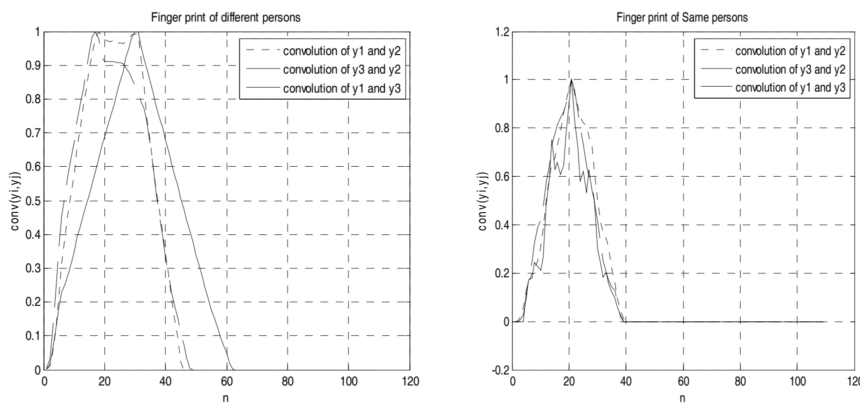
(b) Method 2

Fig. 3. Convolution vectors y_i and y_j for the same person (after normalization)



(a) Method 1 (b) Method 2

Fig. 4. Fingerprints and corresponding 9th level approximations of A for the different person



(a) Method 1 (b) Method 2

Fig. 5. Convolution vectors of y_i and y_j for different persons (after normalization)

sponding convolution vectors (in normalized form) are plotted in Fig. 5. Both the methods show wide deviation as is seen from Fig. 4 and Fig. 5.

In this section, we also consider three statistical parameters: 1) skewness, 2) kurtosis, and 3) Cross correlation co-efficient of vectors y_1, y_2 and y_3.and an A comparison is made between the two methods on these parameters as is shown in Table 1 and Table 2.

All the parameters for same and different person cases are shown in Table 1 for the Method 1cases. The cross correlation-coefficient for the same person case is almost 98% and the different person case is below 89%. The maximum deviation of statistical parameters of three images (for the same person and different person cases) is shown in Table 3 below.

We observe from Table 3, that in Method 2, the percentage of deviation from statistical parameters for fingerprints of the same person is much lower than Method 1. On the other hand, the percentage of deviation for the same parameters in method 2 is much higher in the different person case compared to that of Method 1 except for the cross-correlation coefficient. In context of percentage of deviation from statistical parameters, Method 2 is better than Method 1.

Table 1. Comparison of statistical parameters (Method 1)

Vectors	Same person			Different persons		
	Skewness (yi, yj)	Kurtosis (yi, yj)	Cross correlation co-efficient of *yi* and *yj*	Skewness	Kurtosis	Cross correlation of *yi* and *yj*
y_1 and y_2	1.3569	3.1339	0.9646	1.3569	3.1339	0.5745
y_2 and y_3	1.2921	2.7439	0.9810	0.1924	1.2080	0.6532
y_1 and y_3	1.4195	3.4461	0.9646	0.4879	2.3120	0.8859

Table 2. Comparison of statistical parameters (Method 2)

Vectors	Same person			Different persons		
	Skewness (yi,yj)	Kurtosis (yi,yj)	Cross correlation co-efficient of *yi* and *yj*	Skewness	Kurtosis	Cross correlation of *yi* and *yj*
y_1 and y_2	1.0791	2.2164	0.9999	1.0799	2.2176	0.7919
y_2 and y_3	1.0793	2.2187	0.9999	1.0568	7.4651	0.8373
y_1 and y_3	1.0799	2.2176	0.9999	-0.9441	12.5440	0.7414

Table 3. Maximum deviation of Skewness, Kurtosis, and cross correlation

Method	Same person			Different persons		
	Maximum deviation of Skewness (d_s)	Maximum deviation of Kurtosis (d_k)	Maximum deviation of Cross correlation (d_c)	Maximum deviation of Skewness (d_s)	Maximum deviation of Kurtosis (d_k)	Maximum deviation of Cross correlation (d_c)
Method 1 (Table 1)	8.9750%	20.3767%	1.6718%	85.8206%	61.4538%	35.1507%
Method 2 (Table 2)	0.0741%	0.1037%	0%	187.4248%	82.3214%	11.4535%

4. CONCLUSION

This paper makes a comparison of two proposed methods for detection of fingerprints. Method 2 reveals better results in context of all statistical parameters. The results section of this paper considers only three fingerprints in the process of finding similarities and dissimilarities. Before proceeding towards materialization of the model proposed here for real life practicality it has to be tested for thousands of fingerprints. Still there is scope for extension of the paper involving filtering the images using different types of filters used in image processing (here we used only Canny filters) to increase contract so that the edges of the image become sharper and finally, color inversion will produce images of dark lines on a white background. Then the entire previously described analysis can be repeated to observe and compare performance.

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APPENDIX A

In wavelet analysis, we often speak of *approximations* and *details*. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. *Approximations* and *details* of *f (t)* are evaluated like [3, 9]:

The average values of *f (t)* over corresponding intervals are obtained as,

$$C(m,n) = \frac{1}{2^m} \int_{2^m n}^{2^m (n+1)} f(t)dt \tag{A1}$$

$$d(m,n) = \frac{1}{2^m} \int_{2^m n}^{2^m (n+1)} f(t)\psi(2^{-m} t - n)dt\ . \tag{A2}$$

Let $f_k(t)$ be the piece wise constant over the interval of length 2^k known as approximation to *f(t)* expressed as,

$$f_k(t) = \sum_{l=-\infty}^{\infty} c(k,l)\phi(2^{-k} t - l)\ ,$$

where

$$\phi(t) = \prod (t - 1/2)\ . \tag{A3}$$

Again the detail function at level *k* is expressed as,

$$g_k(t) = f_{k-1}(t) - f_k(t) = \sum_{l=-\infty}^{\infty} d(k,l)\psi(2^{-k} t - l)\quad . \tag{A4}$$

A two level decomposition of a sequence *x (n)* of 800 samples is shown in Fig.5. At each level, the HP filter produces the sequence of coefficients called detail information, d(i, n), while the LP filter produces a sequence *a(i, n)* called approximations.

Example 1

Let us consider a function $f(t)=e^{-t/4}u(t)$; where *u(t)* is a unit step function. The piece wise constant $f_k(t)$ and the detail function $g_k(t)$ for different values of k are plotted in Fig. 6. A two-dimensional discrete wavelet transform is one of the prominent mathematical tools to resolve components of an image for analysis and modification [10, 11].

Let us consider a square and integral function *f(x,y)* can be expressed as a linear combination of three two-dimensional wavelets – namely, $S_{\Phi\Psi}(x, y)$, $S_{\Psi\Phi}(x, y)$ and $S_{\Psi\Psi}(x, y)$ like,

$$f(x,y)=\sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty}\sum_{n=-\infty}^{\infty}\sum_{p=-\infty}^{\infty} b_k(n,p)s_{\phi_\psi}(2^{-k}x-n,2^{-l}y-p)$$
$$+\sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty}\sum_{n=-\infty}^{\infty}\sum_{p=-\infty}^{\infty} c_k(n,p)s_{\psi_\phi}(2^{-k}x-n,2^{-l}y-p) \qquad \text{(A5)}$$
$$+\sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty}\sum_{n=-\infty}^{\infty}\sum_{p=-\infty}^{\infty} d_k(n,p)s_{\psi_\psi}(2^{-k}x-n,2^{-l}y-p),$$

where the coefficient $b_k(n,p)$, $c_k(n,p)$ and $d_k(n,p)$ can be evaluated based on [10-12]. The skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable X express as,

$$\gamma=E\left[\left(\frac{X-\mu}{\sigma}\right)^3\right]=\frac{\mu_3}{\sigma^3}=\frac{E[X^3]-3\mu\sigma^2-\mu^3}{\sigma^3}, \qquad \text{(A6)}$$

where μ is the mean and σ is the standard deviation of the random variable *X*. The kurtosis is a measure of the ‘peakedness’ (the ratio of variance and mean) of the probability distribution of a real-valued random variable which is equal to the fourth moment around the mean divided by the square of the variance of the probability distribution minus 3:

$$\kappa=\frac{\mu_4}{\sigma^4}-3\,. \qquad \text{(A7)}$$