An Accurate and Fast Automatic Fingerprints Verification Technique

H. Kasban

Engineering Department, Nuclear Research Center,
Atomic Energy Authority,
Inshas, Egypt
E-mail: Hany_kasban@yahoo.com

Abstract:

This paper presents a proposed automatic fingerprint verification technique. The proposed technique consists of two phases; a training phase and a testing phase. In the training phase, firstly, image enhancement process is carried out using Adaptive Histogram Equalization (AHE) and Gabor filter, then, the Higher Order Statistics (HOS) of the image are estimated. The local and global features are extracting from each image or from its HOS. These features are used to train Support Vector Machines (SVMs) consisting of features database. In the testing phase, the features are extracted from every incoming image with or without image blurring or rotation and a feature matching step is performed to decide whether these features belong to the same person or not. The simulation results achieved up to 98% verification rate and proved that the proposed technique can be used in a reliable way for automatic fingerprint verification in the presence of image blurring or rotation.

Keywords-component: Fingerprint Verification, SVMs, HOSs, Gabor Filter.

I. INTRODUCTION

Fingerprint matching is one of the most common and reliable method used in personal identification [1]. The fingerprints patterns of any person are individual and remain unchanged throughout life. Nowadays fingerprints matching process is running automatic for searching inside the stored database. There are two main applications for fingerprints; the first application is the fingerprint verification that used to verify the identity of a person [2] as shown in figure (1-a). The second application is the fingerprint identification that used to establish the identity of a person, it involves matching a query fingerprint against a fingerprint database to establish the identity of an individual [3, 4] as shown in figure (1-b).
There are many methods can be used for personal identification such as; Speaker recognition, face recognition, Iris recognition, fingerprint recognition, hand geometry, signature recognition. The advantages of using fingerprints in personal identification are;

- Fingerprint will remain unchanged during lifetime.
- Fingerprint is an individual characteristic and no two fingers have identical ridge characteristics.
- Fingerprints have general ridge patterns, making it possible to systematically classify them.
- Fingerprinting is still a viable means for biometric identification, especially in law enforcement, where fingerprints may be left behind.
- Fingerprints offer a cheaper solution for day-today activities than the other recognition methods.

The limitations of using fingerprints in personal identification are;

- Fingerprints are not as good for high-security implementation.
- More work needs to be done to develop better methods to compensate for the variations in fingerprint recording when identifying local features.

Fingerprint image verification process has been studied by several researchers using various techniques and approaches [6-17]. Automatic recognition of people based on fingerprints requires that the input fingerprint be matched with a large number of fingerprints in a database [5]. To reduce the search time and computational complexity, it is desirable to classify these fingerprints in an accurate and consistent manner so that the input fingerprint is required to be matched only with a subset of the fingerprints in the database. Fingerprint is a pattern of curving line structures called ridges (black color), where the skin has a higher profile than its surroundings, which are called the valleys (white color). The unique pattern of lines can either be loop, whorl, or arch pattern. Valleys are the spaces or gaps that are on either side of a ridge. Some common classes of fingerprint sets are shown in figure (2).

![Figure 2. Common classes of fingerprint.](image)

The rest of this paper is organized as follows. Section 2 presents the proposed automatic fingerprints verification technique. Section 3 gives the simulation results. Finally, Section 4 gives conclusions remarks.
II. PROPOSED AUTOMATIC FINGERPRINTS VERIFICATION TECHNIQUE

The proposed automatic fingerprints verification technique is shown in figure (3), it consists of two phases; a training phase and a testing phase. In the training phase, firstly, an enhancement process is carried out using AHE and Gabor filter, then, the HOS of the image are estimated. Features are extracting from each image or from its HOS. These features are used to train SVMs consisting of features database. In the testing phase, the features are extracted from every incoming image with or without image blurring or rotation and a feature matching step is performed to decide whether these features belong to the same person or not. The steps of the proposed technique will discuss with details in the following subsections.

![Block diagram of automatic fingerprints verification process.](image)

A. Fingerprint Image Quality Enhancement

Fingerprint images enhancement is important process for a good performance of automatic Fingerprint verification. In this paper, AHE and Gabor filter are used for fingerprint image enhancement. Histogram equalization is used to improve fingerprint image contrast in [18-19]. The histogram equalization transforms the intensity values of the image (the values in the color map of an indexed image) as in the following equation [18]:

\[ s_i = T(r_i) = \sum_{j=1}^{n} p_i (r_j) = \sum_{j=1}^{n} \frac{n_j}{n} \]  

(1)

Where \( S_i \) is the intensity value in the processed image corresponding to \( r_i \) in the input image, and \( p_i (r_j) =1, 2, 3... L \) is the input fingerprint image intensity level.

Histogram equalization may be amplify the background noise through the transformation of the intensity values and produce lower quality image for some fingerprints, so that, the AHE is made adaptively by taking the histogram over a local region instead of the whole image to enhance the contrast of small tiles and to combine
the neighbouring tiles in an image by using bilinear interpolation, which eliminates the artificially induced boundaries. After AHE, the image passes into a filtering step using Gabor filter. Gabor filter capture both the local orientation and the frequency information from the fingerprint image. By tuning Gabor filter to specific frequency and direction, the local frequency and orientation information of the fingerprint can be obtained. Gabor filter has the following form in the spatial domain [20]:

\[
G(x, y; f, \theta) = \exp\left[-\frac{1}{2}\left(\frac{x^2}{\delta_x^2} + \frac{y^2}{\delta_y^2}\right)\right] \cos(2\pi f x)
\]

\[x' = x\sin(\theta) + y\cos(\theta)\]

\[y' = x\cos(\theta) - y\sin(\theta)\]

where \(f\) is the frequency of the sinusoidal plane wave along the direction \(\theta\) from the x-axis, and \(x_\delta\) and \(y_\delta\) are the space constants of the Gaussian envelope along x and y axes, respectively.

**B. Higher Order Statistics Estimation**

HOS are extensions of second-order measures such as the power density spectrum (PDS) and the autocorrelation function. The third-order statistics (Bispectrum) is the decomposition of the third moment (skewness) of a signal over frequency, it represents the Discrete Fourier Transform (DFT) of the triple correlation [21]. The fourth-order statistics (Trispectrum) is the decomposition of the fourth moment (kurtosis) over frequency, it represents the DFT of the fourth correlation. The advantages of HOS over PDS are; no phase information in PDS, this leads to; non-minimum phase signals cannot be correctly identified by PDS, and the phase coupling cannot be correctly identified using PDS. HOS are less affected by Gaussian background noise less than the PDS. The \(n\)th-order correlation of signal \(f(x)\) is defined as [22]:

\[
f_n(\tau_1, \tau_2, ..., \tau_{n-1}) = \sum_{k=0}^{N-1} f(x) f(\tau_1 + x) f(\tau_2 + x) ... f(\tau_{n-1} + x)
\]

Where, the \(n\)th order correlation is a function of \((n-1)\) independent variables. For \(n=2\), the above equation becomes the second-order correlations of \(f(x)\) which is the familiar autocorrelation function. The third-order correlation \((n=3)\) of a one dimensional function is a function of two variables. From the equation the third-order correlation of \(f(x)\) is:

\[
f_3(\tau_1, \tau_2) = \sum_{k=0}^{N-1} f(x) f(\tau_1 + x) f(\tau_2 + x)
\]

Where \(f_3(t_1, t_2)\) is symmetric with respect to its variables \(t_1\) and \(t_2\). The third-order correlation coefficient \(f_3(0,0)\) can be found by sampling the triple correlation \(f_3(t_1, t_2)\) at zero displacement where \(t_1 = t_2 = 0\). From the equation the third-order correlation coefficient becomes:

\[
f_3(0,0) = \sum_{k=0}^{N-1} f^3(x)
\]

The third-order correlation coefficient \(f_3(0,0)\), of \(f(x)\) can be calculated directly as the sum of the cubes of \(f(x)\) from \(k=0-N-1\).
C. Fingerprint Feature Extraction

In this paper three categories of features are used for fingerprint representation; global, local, and image based features. Global features describe the flow structure of the image and they are the characteristics that can see by human eye such as; the ridge patterns (loop, arch, whorl, …. , etc. as shown above in figure (2)), pattern area, type lines, ridge count, core point, meeting of two ridges, dot, fragmentary ridge, and singular points. Figure (4) show some of these features.

![Feature Images](image1.png)

(a) Core point (b) Type lines (c) Ridge count (d) Singular points

Figure 4. Some of common fingerprint global features.

The local or minutiae features describe the minute details of ridges. They are the unique characteristics of fingerprint ridges that are used for positive identification such as ridge ends, ridge bifurcation, short ridge, and ridge divergence as shown in figure (5).

![Feature Images](image2.png)

Figure 5. Some of common fingerprint local features.

Image based features uses the visual appearance of the image such as color, shape, and texture of the image. Color features can be obtained easily from the pixel intensities. Shape features represent the image edges, corners, and other structures. Texture based features uses the texture information of the image and treats the fingerprint image as an oriented texture image such as statistics of the gray-level histogram, and moment-based features.

D. Fingerprint Feature Matching using SVM

The support-vector machine is a learning machine used for two-group classification problems [23-24]. The basic SVM deals with two-class problems in which the data are separated by a hyperplane defined by a number of support vectors. It operates by mapping the data of interest to a high dimensional space and generating a separating hyperplane in that space. The high dimensional separating hyperplane can be used for hypothesis testing. The verification using SVMs composed of two processes: building a model that simulates the verification technique and a feature matching process that evaluates the performance of the model by using a test set of images. In the modeling step, the fingerprint images are stored to the system using features that are extracted during the training phase. When an unknown set of signal arrive, a feature matching technique is applied to map the features from this set to the model. SVMs minimize the empirical identification error and
maximize the geometric margin. SVMs map an input vector to a higher dimensional space, where a maximal separating hyperplane is constructed. Two parallel hyperplanes are constructed on each side of the hyperplane that separates the data. The separating hyperplane is the hyperplane that maximizes the distance between the two parallel hyperplanes.

III. SIMULATION RESULTS

To evaluate the performance of the proposed technique, publicly available fingerprint databases are used. Three from the International Fingerprint Verification Competitions (FVCs) databases have been used (FVC2000, FVC2002 and FVC2004) [25-27]. For each competition, four databases were acquired using different scanner as summarize in table (1) [28-30].

<table>
<thead>
<tr>
<th>Competitions</th>
<th>Database</th>
<th>Sensor type</th>
<th>Image Size</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>FVC 2000</td>
<td>DB1</td>
<td>Low-cost optical sensor</td>
<td>300x300</td>
<td>500 dpi</td>
</tr>
<tr>
<td></td>
<td>DB2</td>
<td>Low-cost capacitive sensor</td>
<td>256x364</td>
<td>500 dpi</td>
</tr>
<tr>
<td></td>
<td>DB3</td>
<td>Optical sensor</td>
<td>448x478</td>
<td>500 dpi</td>
</tr>
<tr>
<td></td>
<td>DB4</td>
<td>Synthetic generator</td>
<td>240x320</td>
<td>500 dpi</td>
</tr>
<tr>
<td>FVC 2002</td>
<td>DB1</td>
<td>Optical sensor</td>
<td>388x374</td>
<td>500 dpi</td>
</tr>
<tr>
<td></td>
<td>DB2</td>
<td>Optical sensor</td>
<td>296x560</td>
<td>509 dpi</td>
</tr>
<tr>
<td></td>
<td>DB3</td>
<td>Capacitive sensor</td>
<td>300x300</td>
<td>500 dpi</td>
</tr>
<tr>
<td></td>
<td>DB4</td>
<td>SFINGE V2.51</td>
<td>288x384</td>
<td>500 dpi</td>
</tr>
<tr>
<td>FVC 2004</td>
<td>DB1</td>
<td>Optical sensor</td>
<td>640x480</td>
<td>500 dpi</td>
</tr>
<tr>
<td></td>
<td>DB2</td>
<td>Optical sensor</td>
<td>328x364</td>
<td>500 dpi</td>
</tr>
<tr>
<td></td>
<td>DB3</td>
<td>Thermal sweeping Sensor</td>
<td>300x480</td>
<td>512 dpi</td>
</tr>
<tr>
<td></td>
<td>DB4</td>
<td>SFINGE V3.0</td>
<td>288x384</td>
<td>500 dpi</td>
</tr>
</tbody>
</table>

The image enhancement process is carried out for all images examples of the effect of the enhancement are shown in figure (6).

Figure 6. Examples of enhancement images.
For quantitative evaluation of the enhancement process, three metrics are used; entropy, uniformity, and smoothness. The Entropy is the statistical measure of the randomness, it used for characterizing the texture of the input image. The Entropy \(E\) is defined as [31]:

\[
E = \sum p(x_i) \log_2 p(x_i)
\]  

where \(x_i\) is the pixel value , and \(p(x)\) is the histogram of the intensity levels in the region of interest. The Uniformity is the consistency in ridges and valleys gray levels. The Uniformity \(U\) defined as [31]:

\[
U = \sum p^2(x_i)
\]

The smoothness measures the relative smoothness of the intensity in a region and indicates the average contrast of the images. The Smoothness \(S\) defined as [31]:

\[
S = 1 - \frac{1}{1 + \sigma^2}
\]

where \(\sigma^2\) is the image variance. The above metrics are calculated for one image (the first image) from each FVCs database, the results are summarized in table (2).

Table 2. Quantitative evaluation of the fingerprint enhancement process

<table>
<thead>
<tr>
<th>Comp.</th>
<th>Metrics</th>
<th>Image Database</th>
<th>Entropy(E)</th>
<th>Uniformity(U)</th>
<th>Smoothness(S)</th>
<th>Processin g Time (Sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>original</td>
<td>After AHE</td>
<td>After filter</td>
<td>original</td>
</tr>
<tr>
<td>FVC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td></td>
<td></td>
<td>6.0154</td>
<td>6.9158</td>
<td>6.9634</td>
<td>0.0083</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>5.0000</td>
<td>5.0750</td>
<td>5.2457</td>
<td>0.1466</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>6.9048</td>
<td>6.9187</td>
<td>6.9749</td>
<td>0.0268</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4.8419</td>
<td>4.8991</td>
<td>4.9627</td>
<td>0.1969</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FVC</td>
<td></td>
<td></td>
<td>3.2882</td>
<td>3.2882</td>
<td>3.4259</td>
<td>0.4770</td>
</tr>
<tr>
<td>2002</td>
<td></td>
<td></td>
<td>7.1804</td>
<td>7.2184</td>
<td>7.4105</td>
<td>0.0082</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>6.7072</td>
<td>6.7074</td>
<td>6.7671</td>
<td>0.0116</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>7.0786</td>
<td>7.0838</td>
<td>7.1594</td>
<td>0.0096</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FVC</td>
<td></td>
<td></td>
<td>7.2882</td>
<td>7.2882</td>
<td>7.3259</td>
<td>0.4770</td>
</tr>
<tr>
<td>2004</td>
<td></td>
<td></td>
<td>6.6614</td>
<td>6.6917</td>
<td>6.7824</td>
<td>0.0237</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4.9684</td>
<td>4.9684</td>
<td>5.0819</td>
<td>0.0874</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>6.9027</td>
<td>6.9512</td>
<td>6.9758</td>
<td>0.0112</td>
</tr>
</tbody>
</table>

The above results show that the fingerprint enhancement algorithm succeeds in the enhancement of the fingerprints and achieves better results. The results of the overall verification process are summarized in table 3. Image blurring is carried out using 3 order low pass filter, and the image rotation is 45°.

Table 3. Percentage verification rate for different FVCs database

<table>
<thead>
<tr>
<th>Comp.</th>
<th>Database</th>
<th>Features from image</th>
<th>Features from Bispectrum</th>
<th>Features from Trispectrum</th>
<th>Features from image</th>
<th>Features from Bispectrum</th>
<th>Features from Trispectrum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Enhanced image</td>
<td>With image blurring</td>
<td>With image rotation</td>
<td>Features from image</td>
<td>Features from Bispectrum</td>
<td>Features from Trispectrum</td>
</tr>
<tr>
<td>FVC</td>
<td>2000</td>
<td>DB1</td>
<td>96</td>
<td>95</td>
<td>96</td>
<td>91</td>
<td>94</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB2</td>
<td>81</td>
<td>81</td>
<td>83</td>
<td>80</td>
<td>77</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB3</td>
<td>93</td>
<td>92</td>
<td>93</td>
<td>91</td>
<td>89</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB4</td>
<td>71</td>
<td>74</td>
<td>79</td>
<td>70</td>
<td>72</td>
</tr>
<tr>
<td>FVC</td>
<td>2002</td>
<td>DB1</td>
<td>97</td>
<td>97</td>
<td>98</td>
<td>91</td>
<td>96</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB2</td>
<td>95</td>
<td>95</td>
<td>95</td>
<td>94</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB3</td>
<td>96</td>
<td>97</td>
<td>97</td>
<td>95</td>
<td>96</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB4</td>
<td>54</td>
<td>51</td>
<td>55</td>
<td>52</td>
<td>50</td>
</tr>
<tr>
<td>FVC</td>
<td>2004</td>
<td>DB1</td>
<td>54</td>
<td>51</td>
<td>55</td>
<td>52</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB2</td>
<td>92</td>
<td>92</td>
<td>94</td>
<td>93</td>
<td>91</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB3</td>
<td>76</td>
<td>76</td>
<td>77</td>
<td>72</td>
<td>74</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DB4</td>
<td>94</td>
<td>95</td>
<td>95</td>
<td>91</td>
<td>93</td>
</tr>
</tbody>
</table>
The above results show that, the features extracted from the trispectrum of the image gives the higher verification rate, the verification process is affected by the image blurring more than the image rotation.

IV. CONCLUSIONS

This paper presented a novel automatic fingerprint verification technique based on HOS and SVM. The fingerprint image has been enhanced using adaptive histogram equalization and Gabor filter. Local, global, and image based features are extracting from the fingerprint image or from its HOSs. SVMs have been used in training and matching processes. The proposed technique performance has been evaluated with or without image blurring or rotation using FVCs databases. The results achieved up to 98 % verification rate. The results show that the proposed technique can be used in a reliable way for automatic fingerprint verification in the presence of image blurring or rotation.

REFERENCES


