An Efficient Spatially Invariant Model for Fingerprint Authentication based on Particle Swarm Optimization

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ABSTRACT

Accurate and reliable fingerprint recognition is a challenging task, which heavily depends on the quality of the fingerprint images. It is well-known that the fingerprint recognition systems are very sensitive to noise and other image transformations such as rotation. In this paper, a Biometric Fingerprint authentication algorithm using a particle swarm optimization (PSO) based feature selection approach is proposed to address the above issues. The search in PSO is iteratively guided by a fitness function defined to maximize class separation to identify new features instead of the traditional Minutiae (Termination and Bifurcation features). The first contribution is the formulation of a new feature selection algorithm for fingerprint recognition based on the DWT algorithm, which solves the localization problem by applying PSO separately to four sub-bands to increase the recognition rate and to speed up feature selection. The second contribution is an invariant moment matching algorithm which is proposed as a matching algorithm to address some misclassified features and to increase the matching accuracy. The proposed algorithm was found to generate excellent recognition results which admit 100% accuracy when applied on the FCV2002, 2004 and 2006 dataset. Also it admits accuracy ranged 96.35-100% when applied to fingerprints with a rotation of 0-360º.

Keywords: Authentication system, Swarm Intelligence, PSO, Invariant moment matching algorithm.

INTRODUCTION

Recognition of a person by means of biometric characteristics is an emerging technology. Among the possible biometric traits like face, iris, speech, and hand geometry, fingerprint is the most widely used trait, because of its distinctiveness and persistence over time [1].

A fingerprint image is a pattern of ridges and valleys, with ridges as dark lines while valleys as light areas between the ridges. Ridges and valleys generally run parallel to each other, and their patterns can be analyzed on a global and local level [2]. Global analysis of the fingerprint image is done to extract singular regions like loop, delta, and whorl. Many matching algorithms use the center of the highest loop type singularity, known as the core, to pre-align fingerprint images for better results. These singularities help form the 5 major classes [3] of fingerprints.

The noise and other distortion during the acquisition of the fingerprint and errors in the minutia extraction process can result in spurious and missing minutiae that easily degrade the performance of the recognition. Another problem is that the rotation and displacement of the finger placed on the sensor, can lead to different images for the same fingerprint such that they have only a partial overlap area resulting in only a small number of corresponding minutiae points [5]. The problems with minutia extraction can be more severe if the fingerprint is acquired using a compact solid-state sensor. They provide only a small contact area for the fingertip and, therefore, capture only a limited portion of the fingerprint pattern [6].

A practical biometric system should meet the specified recognition accuracy, speed, and resource requirements, be harmless to the users, be accepted by the intended population, and be sufficiently robust to various fraudulent methods and attacks to the system [3]. It is difficult to reliably obtain the minutia points from poor quality fingerprint images or from small sensor images. The situations become more difficult for noisy and rotated fingerprint images. Therefore, it is highly necessary to exploit novel attributes which are not affected by rotation.
and noise, and develop new methods suitable for partial fingerprint recognition. Matchers based on these attributes can also be used to complement the minutia-based techniques [4]. To this end, we propose a Spatially Invariant Model for fingerprint authentication using particle swarm optimization (PSO) based on wavelet transform and invariance moment function. Unlike most existing studies [5, 6, 7] that rely on Minutiae features, in order to address the negative impact of rotation and noise, we introduce the PSO approach.

Particle swarm optimization is a heuristic global optimization method, which is based on swarm intelligence to select new features, and originated from the research on the bird and fish flock movement behavior. The algorithm is widely used and rapidly developed as it is easy to implement and few particles are required to be tuned. We propose to use PSO to avoid some fingerprint matching problems faced by other approaches such as Minutiae features based. For the feature extractor model, we rely on using a wavelet transform to do multi practical search on the same fingerprint image in different parts simultaneously, selecting different features for different frequency directions which solves the localization problem by making the PSO to move away from the core point (typically located in the center of the fingerprint) to increase the recognition accuracy. For the second model i.e., the matching model, we rely on the invariant moment as a matching algorithm to achieve good accuracy, because the invariance moment function can deal with the feature misclassification problem.

The rest of the paper is organized as follows. Section II discusses some related work and highlights how our approach differs. Section III introduces our proposed system. Section IV shows some experimental results that compare our works with the state-of-the-art approaches, and Section V makes the conclusion.

RELATED WORKS

Most of the previous works for fingerprint recognition use the minutiae features as the fingerprint features. We summarize some related studies below:

Ouzounoglou et al. [5] proposed a fingerprint matching method that was based on the non-necessity of constructing minutiae points in the input fingerprint image. The proposed fingerprint matching algorithm was evaluated using the DB3 database of FVC2004 DB3. The overall performance for fingerprints of the same and different fingers was calculated in terms of the Equal Error Rate (EER) which was equal to 0.0586 and the accuracy rate was 94.1%. Thuy and Thi [6] propose a fingerprint matching method based on local Thin-Plate-Spline (TPS) deformation model. The experimental results on the database FVC2004 show that it significantly improves the matching performance compared to the global TPS warping method. Khan [7] proposes a robust minutia based approach for fingerprint recognition. The proposed strategy is tested on a number of images of publicly available FVC2006 database. Results indicate that the proposed strategy filters the false minutia points reliably.

We observe that the Minutia features based approach has some critical issues according to the requirements of today’s security systems. One is that they are generally time consuming because some of the approaches need to perform some prepossessing such as removing the false features, enhancement like noise removal, and binarization and thinning to extract accurate features as illustrated in Fig.1.b and Fig.1. c. The second one is its sensitivity to geometric transformation of the fingerprint images because it depends on extracting three important parameters which are the x, y locations and the angle value.

Fig. 1: Examples of fingerprint feature extraction, (a): original fingerprint image, (b): false feature based on Minutiae, (c): feature extracted after false feature removing, (d): PSO features

Aly et. al. [8] proposed a new approach for adaptive combination of multiple biometrics using
Particle Swarm Optimization (PSO) to ensure the desired system performance corresponding to the desired level of security. The main advantage of using the PSO features is its simplicity and robustness to geometric transformation of the fingerprint image. In this paper we focused on the enhancement of the PSO feature selection by first using DWT based multi swarm feature extraction, and address some technical issues in previous PSO such as random start position selection, features reduction, and robustness features selection by linking corner points, and then propose an invariance moment algorithm to solve the feature sequence matching problem. Note that Most of the previous works did not discuss about the rotation issue and its effect on the matching accuracy.

THE PROPOSED PSO-BASED SYSTEM

To address the limitations of prior works discussed in Section II, we proposed a PSO based fingerprint authentication system here. PSO provides fast feature search/extraction algorithm and is robust to rotation. The proposed PSO-based fingerprint recognition system is shown in Fig. 2. It consists of six major stages: (i) fingerprint acquisition, (ii) Wavelet transform, (iii) PSO for each sub band to collect different features as shown in Fig 4.c and Fig. 2, (iv) Feature extraction, (v) Moment analysis, and (vi) Matching.

Swarm Intelligence (SI) and PSO Algorithm

Swarm Intelligence (SI) is part of artificial intelligence. In practice, the main aim of AI during the last four decades has been to develop “intelligent machine” with the capabilities to solve complex task similar to human beings. It is based on the study of collective behavior in decentralized and self-organized systems. The idea of SI comes from systems found in nature, including ant colonies, bird flocking and animal herding that can be effectively applied to computationally intelligent system.

SI systems are typically made up of a population of agents interacting locally with one another and with their environment, and local interactions between such nodes often lead to the emergence of a global behavior [8]. The basic PSO model consists of a swarm of particles, which are initialized with a population of random candidate solutions.

They move iteratively through the d-dimension problem space to search for the new solutions, where the fitness function, f, can be calculated as the quality measure [5]. The PSO system is initialized with a population of random solutions and searches for the optima by updating the local maximum value and comparing it with the global maximum. Each particle has a position represented by a position-vector \( x_i \) (\( i \) is the index of the particle), and a velocity represented by a velocity-vector \( v_i \).

Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) achieved so far. This fitness value which depends on the feature position is...
denoted as $p_{\text{best}}$ (globally best) is another value that is tracked by the particle swarm optimizer which is the best fitness value among all the particles in the entire swarms with a random weighted acceleration at each iteration.

During the iteration time $t$, the update from the previous velocity to the new velocity is determined by Eq. (1) below [9]. The new position ($x_{id}$) is then determined by the sum of the previous position and the new velocity, as shown in Eq. (2) [10].

$$V_{(id+1)} = w \times V_{id} + c_1 \times r_1 \times (p_{\text{best}} - x_{id}) + c_2 \times r_2 \times (g_{\text{best}} - x_{id})$$  

$$x_{(id+1)} = x_{(id)} + V_{(id+1)}$$  

1) Better results with faster search (using multi PSO searching).
2) A lower preprocessing computational cost, avoiding fingerprint smoothing, Binarization, ROI (region of Interest), false features removing in minutia features based approach.

The basic algorithm for the Particle Swarm Optimization can be described in Algorithm (1), see Fig.1.c, [9]:

**Algorithm (1) Particle Swarm Optimization algorithm**

**Input:** Initialize parameters  
**Output:** Initialize population

1. **While** stopping criterion is not met  
2. **For** (Number of particles $N$) **do**  
3. **If** the fitness of $t(i) > (i_{\text{best}})$  
4. update $t(i_{\text{best}}) \leftarrow t(i_{x})$  
5. **If** the fitness $t(i_{x}) > g_{\text{best}}$.  
6. update $g_{\text{best}} \leftarrow t(i_{x})$.  
7. **Update** velocity vector.  
8. **Update** particle position.  
9. **Next** particle.  
10. **Next** generation.

**Improving the PSO efficiency**

The original PSO approach [11] to optimize the solution using global maximum but there is a chance that the solution will get trapped in a local area. A Modified Particle Swarm Optimizer [12] works better. There is difficulty in selecting probable initial position. So there are some limitations which affect the accuracy of the PSO. The first one is initial position, and the second limitation is the searching redundancy. To make the PSO feature extraction process more efficient and accurate we propose the following improvements to the original PSO algorithm:
1) Centralization: In this step we propose to let the PSO start from the center of the fingerprint image. The fingerprint has many local maximum, yet the original PSO depends on selecting just one local maximum and evaluate it with the rest of the features. To avoid misclassification due to mismatched initial point of PSO, we propose to perform this centralization step. Note that from our observation there is still an issue of center synchronization between the fingerprint image and the candidates, so we propose to address this center synchronization problem by using an invariance moment algorithm which can take care of the difference between the extracted fingerprint features and the candidate features.

2) Redundancy avoidance: According to the PSO steps shown in algorithm (1), the PSO is going to select the same feature point after some iteration, and that affects the performance of the PSO in speed, so we make sure the PSO doesn’t select the same feature that it selected before based on its position X and Y.

3) Enhancement on PSO Features Extraction: Through our test on the original PSO, we observe that after the data shifting step of the PSO and the position updating, the PSO is going to lose some features which were shifted to the other side of the features matrix, and the PSO is not able to see those according to its searching mask which is 3x3, so we propose to use a circular array and full edge connection to make sure that the PSO has a good chance to see all the good features in the same iteration to improve the performance, as shown in and Fig.3.d and Fig.4.

Robust features selection: In this step we propose a feature separation concept which relies on using the DWT as a transform to make the PSO move away from the center of the fingerprint to solve the localization problem. Because of the centralization step we proposed, we have a potential problem in the feature selection model: note that the PSO may lose some features because of the rotation and noise. So instead of making the PSO to rely on one region to extract the features, we propose to use the DWT to make the PSO move away from the center by selecting different features using one particle swarm in each sub-band so in total we use four particle swarms in four sub-bands in each fingerprint image.

![Fig. 3: A DWT for the fingerprint image with the PSO separation, (a): original fingerprint image, (b): DWT image, (c): different search direction of the PSO for the LL, LH, HL and HH sub bands, (d) the PSO features selection with rows and columns connection](image)

![Fig. 4: Circular data structure which is used to improve the PSO feature extraction, (a): row connection after the shifting process, (b): Column connection after the shifting process.](image)

**Discrete Wavelet Transform (DWT)**

In this step wavelet transform is used to get an efficient image representation that characterizes the significant image features in compact form. Two-dimensional discrete wavelet transform (2-D DWT) decomposes a gray-level fingerprint image into one average component sub-band and three detail component sub-bands. The first sub-band is
denoted as LL and contains the average components, the second sub-band is denoted as LH and contains vertical edges, and the third sub-band is denoted as HL and contains horizontal edges, and the fourth HH sub-band contains diagonal edges. Features Extraction using PSO is then applied. In this step, the PSO technique is used for extracting the features from the fingerprint image according to Algorithm (1). Four set of features are extracted by the PSO algorithm from the four sub bands (LL, LH, HL, and HH).

The proposed PSO with the harr DWT is described in the block diagram of Fig. 2.b. During an iteration of the algorithm, the best local position and the global best position are updated if a better solution is found. The process is repeated till the specified numbers of iterations are exhausted. The number of iterations that is used in the proposed system to find accurate features is 500, which has been found to be able to almost cover all the important features in each fingerprint image.

**Invariant Moment Matching**

Moment invariants have been frequently used as features for image processing, remote sensing, shape recognition and classification. Moments can provide characteristics of an object that uniquely represent its shape. Invariant shape recognition is performed by classification in the multidimensional moment invariant feature space. Several techniques have been developed that derive invariant features from moments for object recognition and representation. It was Hu [14] that first set out the mathematical foundation for two-dimensional moment invariants and demonstrated their applications to shape recognition.

The proposed system relies on the matching operation for granting the recognition. The matching is to match the target person with all people that have enrolled in the database. When the matching (between the database LL features and the extracted LL features) ratio is lower than a first threshold value the person is unauthorized. When it is equal or greater than 98%, the person is authorized. When it is larger than the first threshold, but lower than 98%, then another comparison between (databases LH, HL, HH features and candidate LH, HL, HH features) is done. If the result of the second comparison is equal or greater than 90% then the person is authorized otherwise the person is unauthorized. The most important advantage of the proposed matching algorithm is that the invariance moment algorithm is going to admit the features which are in the same range, i.e., the fitness values of these features are the same.

We make use of the following basic number theory [14] [15] to address the issue of PSO misclassified features, i.e., the PSO may lose some features (the extracted features are not exactly the same as the candidate ones) in the presence of rotation and noise. Depending on the number theory that the invariance moment relies on, when the difference in fitness value between two sets of features is still within a threshold, they are considered as the same.

**Algorithm (2) Invariance moment matching algorithm**

| Input: PSO fingerprint candidate features x[i]. |
| Output: Return matching accuracy by comparison the two set of features between the stored fingerprint image and the extracted one. |
| 1. For each data in stored features y[i] |
| 2. For i = 0... (Number of features) do |
| 3. \( \alpha \leftarrow x[i] \times 0.5 \) |
| 4. lower_range \( \leftarrow x[i] - \alpha \) |
| 5. high_range \( \leftarrow x[i] + \alpha \) |
| 6. If range low \( \leq y[i] \) and range high \( \geq y[i] \) |
| 7. no_check \( \leftarrow \) no_check +1 |
| 8. Until iteration number |

**Theorem:** If \( a \) and \( b \) are positive integers that are mutually prime, there must be two integers \( x' \), \( y' \) that satisfy

\[
ax' + by' = 1
\]  

(3)

Let \( x=bcx' \), \( y=cy' \). Then from Eq. (3), we have
\[ ax + by = (ax' + ay') = c \]  \hfill (4)

Then, if \( a, b \) is mutually prime and \( c \) is an integer, there must exist integer solutions that satisfy Eq. (4). One possible solution of Eq. (4) is

\[ x = cx' \text{ and } y = cy' \]  \hfill (5)

In general, if \( x = cx' \) and \( y = cy' \) forms one set of the solution of Eq. (4), the general solution of Eq. (5) can be written as:

\[ x = cx' - bn \text{ and } y = cy' - an \]  \hfill (6)

Algorithm (2) shows the steps of the invariance moment matching algorithm.

**EXPERIMENTAL RESULTS**

We test and compare the performance of the proposed system to previous works.

**Overall Dataset performance:**

Table 1 shows the performance of our system on two different databases in FCV2006 [15], in comparisons with a previous algorithm which is minutiae features based. Our proposed system provides higher CVR (correct verification rate), much lower EER (false reject rate) and much faster enrollment and matching [16].

**TABLE I**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>DB</th>
<th>CVR</th>
<th>AV EER</th>
<th>AV REG. TIME</th>
<th>AV REMATCH</th>
<th>AV Enrol Time</th>
<th>AV Match Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>96.14%</td>
<td>2.72%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.10 s</td>
<td>3.19 s</td>
</tr>
<tr>
<td>2</td>
<td>100%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.05 s</td>
<td>0.2 s</td>
</tr>
<tr>
<td>1</td>
<td>96.44%</td>
<td>3.56%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.07 s</td>
<td>0.81 s</td>
</tr>
<tr>
<td>2</td>
<td>100%</td>
<td>0.82%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.05 s</td>
<td>0.2 s</td>
</tr>
</tbody>
</table>

**Comparison with another related works:**

Table 3 compares the recognition results obtained by our proposed method with previous studies. Table 5 shows that the performance of the proposed system depending on FAR (false accept rate), FRR (false reject rate), and CAR (correct verification rate), where FAR, FRR, and CAR are defined in Eq.s 7, 8, and 9 [16]:

\[ FAR = \frac{\text{number of false acceptation}}{\text{total number of test sample}} \]  \hfill (7)

\[ FRR = \frac{\text{number of false rejection}}{\text{total number of test sample}} \]  \hfill (8)

**TABLE III**

<table>
<thead>
<tr>
<th>Meth</th>
<th>Dataset</th>
<th>Match</th>
<th>T</th>
<th>PSO Match</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>[14]</td>
<td>FCV2002</td>
<td>100.00%</td>
<td>5.01 s</td>
<td>100.00%</td>
<td>0.1 s</td>
</tr>
<tr>
<td>[15]</td>
<td>FCV2004</td>
<td>97.66%</td>
<td>1.47 s</td>
<td>99.92%</td>
<td>0.1 s</td>
</tr>
<tr>
<td>[16]</td>
<td>FCV2006</td>
<td>96.77%</td>
<td>0.167</td>
<td>100.00%</td>
<td>0.1 s</td>
</tr>
</tbody>
</table>

**TABLE IV**

| Performance components between Proposed and previous PSO [8] |
|------------------|------------------|------------------|------------------|------------------|
| FAR              | 0.00             | FRR              | 0.01             | CVR%             | 99.99           |
| Our Proposed PSO based system | | | | | |
| FAR              | 0.00             | FRR              | 14.50            | CVR%             | 85.50           |
Time complexity:

Table 6 describes the time consumed at each stage of the developed verification system.

<table>
<thead>
<tr>
<th>No</th>
<th>Stages</th>
<th>Minutia</th>
<th>Ratio</th>
<th>Proposed System</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rad image</td>
<td>0.01</td>
<td>0.03%</td>
<td>0.02 sec</td>
<td>0%</td>
</tr>
<tr>
<td>2</td>
<td>Convert to gray</td>
<td>0.01</td>
<td>0.04%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>3</td>
<td>Normalization</td>
<td>0.26</td>
<td>0.32%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>4</td>
<td>Filtering</td>
<td>0.31</td>
<td>1.09%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>5</td>
<td>Binrization</td>
<td>0.05</td>
<td>0.19%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>6</td>
<td>ROI</td>
<td>0.01</td>
<td>0.02%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>7</td>
<td>Island removal</td>
<td>2.44</td>
<td>9.76%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>8</td>
<td>Hole removal</td>
<td>0.88</td>
<td>3.09%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>9</td>
<td>Thinning</td>
<td>0.08</td>
<td>0.27%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>10</td>
<td>Edge Linking</td>
<td>0.05</td>
<td>0.16%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>11</td>
<td>Features Extraction</td>
<td>0.22</td>
<td>0.78%</td>
<td>0.08 sec</td>
<td>0%</td>
</tr>
<tr>
<td>12</td>
<td>Partitioning</td>
<td>23.91</td>
<td>83.6%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>13</td>
<td>Moment Analysis</td>
<td>0 ms</td>
<td>0%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td>14</td>
<td>(matching)</td>
<td>0 ms</td>
<td>0%</td>
<td>0.00 sec</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>Total time</td>
<td>28.58</td>
<td>100%</td>
<td>0.1 sec</td>
<td>100%</td>
</tr>
</tbody>
</table>

Robustness to rotation

Table 6 shows the difference between the Minutia feature based approach and the PSO feature based approach in a rotated fingerprint matching. We have three feature labels: The Green features which are exactly the same, the Yellow features which are not the same but after applying the algorithm (2) which allows the features to be counted as matched features because they are in the same range; and the Red features which are quite different.

The PSO algorithm is more robust in difficult situations according to the matching accuracy, compared to the Minutia features based approach.

Table 7 shows the PSO matching accuracy with different rotated angles which was between 96.08 for 45º and 100 for 180º.

<table>
<thead>
<tr>
<th>No</th>
<th>Sample Rotated</th>
<th>PSO Matching Accuracy</th>
<th>Minutiae Matching Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15º</td>
<td>98.55%</td>
<td>0.00%</td>
</tr>
<tr>
<td>2</td>
<td>45º</td>
<td>96.08%</td>
<td>0.00%</td>
</tr>
<tr>
<td>3</td>
<td>90º</td>
<td>98.81%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

TABLE VI
The mean of the consumed time at each stage and their percentages relative to the total time

TABLE VII
The Matching accuracy FOR ROTATED Fingerprint
CONCLUSION

In this paper we propose a PSO based fingerprint authentication system that provides a number of important functionalities. First, unlike Minutiae features, the PSO features are invariant to rotation, and during the searching process, PSO is going to determine the ROI (region of interest) whereas the other algorithms spent some time to do that. Second, the proposed PSO will directly detect the core point. Third the proposed PSO will collect multi features in different directions by using DWT which solves the localization problem. Finally, the proposed PSO is shown to provide excellent performance, with 100% accuracy in a frontal situation and between 96 to 99.5% in a rotated situation.

REFERENCES