PERFORMANCE EVALUATION OF FINGERPRINT ORIENTATION FIELD RECONSTRUCTION METHODS

Lars Oehlmann, Stephan Huckemann, and Carsten Gottschlich

Institute for Mathematical Stochastics
University of Göttingen
Goldschmidtstr. 7, 37077 Göttingen, Germany
oehlmann, huckeman, gottschlich@math.uni-goettingen.de

ABSTRACT
Orientation fields (OFs) are a key element of fingerprint recognition systems. They are a requirement for important processing steps such as image enhancement by contextual filtering, and typically, they are estimated from fingerprint images. If information about a fingerprint is available only in form of a stored minutiae template, an OF can be reconstructed from this template up to a certain degree of accuracy. The reconstructed OF can then be used e.g. for fingerprint alignment or as a feature for matching, and thus, for improving directly or indirectly the recognition performance of a system. This study compares reconstruction methods from the literature on a benchmark with ground truth orientation fields. The performance of these methods is evaluated using three metrics measuring the amount of reconstruction errors as well as in terms of computational runtime.

Index Terms— Fingerprint orientation field reconstruction, performance evaluation, comparison, fingerprint recognition

1. INTRODUCTION
Orientation fields (OFs) are an indispensable component of almost all fingerprint recognition algorithms. They are used at many processing stages and for various purposes, e.g. for fingerprint alignment [1], singular point detection, fingerprint classification, image enhancement by contextual filtering [2, 3] or descriptor matching. Moreover, OFs are applied for absolute pre-alignment in fingerprint cryptosystems [4], they are used to compute histograms of invariant gradients (HIG) [5] for fingerprint liveness detection and for improving fingerprint recognition performance by score revaluation [6].

The OFs in the aforementioned applications are typically estimated from a fingerprint image. In situations in which only fingerprint minutiae templates are available, OFs can be reconstructed from these templates. This is usually the first step in methods which attempt to reconstruct a fingerprint image from a minutiae template. A survey of such methods is given in [7].

In the context of forensic applications, a law enforcement agency may have a very large database with fingerprints stored as minutiae templates and OFs reconstructed from these templates are useful for the alignment step in latent fingerprint identification as recently analyzed by Krish et al. [8].

Previously, the performance of algorithms for orientation field estimation from fingerprint images has been evaluated using manually marked ground truth orientation information [9, 10]. In this study, we follow this line of work by manually marking minutiae in the images of the FOE benchmark by Turroni et al. [10] and by evaluating the OF reconstruction performance on the ground truth orientation field. To the knowledge of the authors this is the first comparison of OF reconstruction algorithms using direct orientation error measures as described in Section 4 and ground truth OFs.

The following methods will be considered in our comparison.

2. PREVIOUS WORK
Ross, Shah, and Jain (RSJ) [11] have sketched an algorithm for reconstructing a fingerprint image from a minutiae template in 2007 and to this end, they have proposed an OF reconstruction method which considers all possible minutiae triplets in a template. For each pixel, the orientation reconstruction is based on the minutiae triangle with the highest quality according to their definition. We also analyze an alternate version of this method in which we replace their weighted averaging of orientations by an extrinsic mean (e.g. [12]) which we denote as Ross, Shah, and Jain modified (RSJM).

Chen, Zhou, and Yang [13] have suggested in 2009 an OF reconstruction method which inserts virtual minutiae in sparse regions additional to the original minutiae triplets in a template. For each pixel, the orientation reconstruction is based on the minutiae triangle with the highest quality according to their definition. We also analyze an alternate version of this method in which we replace their weighted averaging of orientations by an extrinsic mean (e.g. [12]) which we denote as Chen, Zhou, and Yang modified (CZY1 to CZY4). Their goal is to improve fingerprint matching by combining a minutiae matcher with an orienta-
tion field based comparison algorithm.

Liu et al. (LEA) [14] have proposed an OF reconstruction method in 2011 which regards all minutiae inside a circle with radius \( r \) around the location to be reconstructed. For the weighted averaging of orientations they take not only the distance into account as all other methods do, but also the distance components in parallel and in perpendicular direction, similar to the line sensor method [9]. Liu et al. have conducted a comparison with other methods based on two indirect measures: The reconstructed OF is applied for classification and for OF descriptor based matching. However, it is unclear what kind of orientation reconstruction errors and which amount of error would be tolerable before the prediction, e.g. of a left loop, changes to a different Henry-Galton-class. Therefore, using classification accuracy as an error metric is very imprecise.

Feng and Jain (FJ) [15] have proposed an OF reconstruction method in 2011 which divides the area around a location to be reconstructed into 8 sectors, and considers the nearest minutia in each sector for a distance based weighted averaging of orientations. We also analyze a variant (FJM) which uses the polynomial model of Chen et al. as a final smoothing step.

In the next section, we give a detailed description of the methods considered for OF reconstruction. In Section 4, we explain the evaluation metrics, the ground truth information and the observed results. In Section 5, we conclude with a discussion of the performance comparison.

3. METHODS

3.1. Ross, Shah, and Jain (RSJ)

The algorithm to reconstruct an OF proposed by Ross, Shah, Jain [11] uses so called regular minutia triplets. The reconstruction consists of two steps:

1. Generation of the triplets
2. Estimation of the orientation.

In the first step every minutia triplet is tested for regularity. Regular triangles must meet certain constraints concerning the length of the edges, the difference between the orientations and the interior angles. Each of the regular minutia triplets is assigned with a quality in relation to its average edge length and its maximal difference in the orientation. In a second step the orientation of each pixel that lies in at least one regular minutia-triangle is calculated. For each of those pixels \( P \) the triangle with the highest quality is chosen. Let \( d_i = \text{dist}(m_i, P) \) be the Euclidean distance to the minutiae vertices \( m_i \) with orientation angles \( \theta_i \) (\( i = 1, 2, 3 \)). The orientation at \( P \) is estimated by

\[
\hat{\theta}_P = \frac{d_3d_2}{d_3d_2 + d_1d_3 + d_1d_2} \theta_1 + \frac{d_1d_3}{d_3d_2 + d_1d_3 + d_1d_2} \theta_2 + \frac{d_1d_2}{d_3d_2 + d_1d_3 + d_1d_2} \theta_3,
\]

i.e. the closer the pixel to a vertex, the higher the influence of the vertex’s orientation on the pixel’s orientation.

3.2. Ross, Shah, and Jain modified (RSJM)

In some cases RSJ produces wrong estimations when averaging orientations close to \( 0^\circ \) with orientations close to \( 179^\circ \). Therefore it is reasonable to add a simple modification to the estimation process. Doubling the orientation, transforming the orientation to a vector and performing the weighted averaging with the vector leads to better results, i.e.

\[
\left( \hat{\phi}_{Ps}, \hat{\phi}_{Pc} \right) = \frac{d_3d_2}{d_3d_2 + d_1d_3 + d_1d_2} \left( \sin 2\theta_1 \right) + \frac{d_1d_3}{d_3d_2 + d_1d_3 + d_1d_2} \left( \sin 2\theta_2 \right) + \frac{d_1d_2}{d_3d_2 + d_1d_3 + d_1d_2} \left( \sin 2\theta_3 \right).
\]

The estimated orientation in the pixel \( P \) is given by \( \hat{\phi}_{Ps} = 0.5 \times \arctan(\hat{\phi}_{Ps}, \hat{\phi}_{Pc}) \).

3.3. Chen, Zhou, and Yang (CZY)

Chen, Zhou, and Yang [13] reconstruct the OF using a Delaunay triangulation of the minutiae template and a polynomial model. In complex notation the OF at pixel \((x, y)\) can be represented by the argument of

\[
U(x, y) = \text{RE}(x, y) + i \cdot \text{IM}(x, y).
\]

Then, two bivariate polynomial models

\[
\text{PR}(x, y) = X^T \cdot P_1 \cdot Y
\]

and

\[
\text{PI}(x, y) = X^T \cdot P_2 \cdot Y
\]

with \( X = (x^0, \ldots, x^n) \), \( Y = (y^0, \ldots, y^n) \) are estimated via least squares fits at the minutiae points and additionally at so-called virtual minutiae, to globally model \( \text{RE}(x, y) \) and \( \text{IM}(x, y) \). Virtual minutiae are placed in larger Delaunay triangles and their orientations are weighted averages of the minutiae vertices’ orientations, similar to equation (1).

Each step itself reconstructs an OF, therefore it is adequate to consider all of them in the comparison. The following versions are considered:

- CZY1: We perform Delaunay triangulation and reconstruct each pixel’s orientation directly from those of the three minutiae of the corresponding triplet. No polynomial fitting is performed.
Fig. 1. A good quality example (a) from FOE [10] and its ground truth OF (second and third row of the first column). An overview over the OF reconstruction results (b-j). The second and fifth rows visualize the same reconstructed OFs in gray values between 0 and 179 for the respective orientation in degrees and white pixels denote background. The third and sixth row show the deviation of the reconstructed orientation from the ground truth. Here, white corresponds to $0^\circ$ and the intensity of red increases linearly as the deviation approaches $90^\circ$. 
• **CZY2:** We ignore the interpolation step and fit the polynomial only to the original minutiae.

• **CZY3:** This version implements the full method proposed by [13]. In fact, as the rules for precisely choosing virtual minutiae are not detailed in [13] we proceed to obtain visually highly similar outcomes. Firstly, we perform Delaunay triangulation. Secondly, as long as the size of a triangle exceeds a threshold (we used $t = 608$ pixels), a virtual minutia is inserted and the triangle is divided into three smaller triangles in order to cover sparse areas with additional minutiae. Thirdly, the polynomial model is fitted to the set union of original and virtual minutiae.

• **CZY4:** Firstly, we proceed as in CZY1. Secondly, we additionally fit the polynomial model using all pixels inside the convex hull.

### 3.4. Liu et al. (LEA)

The method proposed by Liu et al. [14] uses the weighted average with a non-symmetric Gaussian weighting function (treating the parallel and the perpendicular deviation differently) of minutiae orientations in a certain radius around the pixel which is being reconstructed. As the convex hull is not fully covered using a pixel radius of $r = 30$ as proposed, in our implementation the radius is increased gradually until the complete convex hull can be reconstructed, and the final smoothing step is omitted.

### 3.5. Feng and Jain (FJ)

The reconstruction algorithm proposed by Feng and Jain [15] divides the minutiae into 8 categories, depending on relative position to the reconstructed pixel (as can be seen in [15] Fig. 10). The weighted average of the closest minutiae in each category weighted with the reciprocal of the distance to the current pixel is then calculated similar to equation (2).

### 3.6. Feng and Jain modified (FJM)

The following modification of FJ has been analyzed for comparability to CZY and in order to explore if an additional, final smoothing step improves the performance of FJ: As in CZY4, we apply the polynomial fitting to all of the points inside the convex hull, but use the OF reconstructed by FJ as orientations at our virtual minutiae points. This method is denoted as FJM.

### 4. RESULTS

The performance of the aforementioned OF reconstruction methods is evaluated on the FOE benchmark set A which consists of 10 images with good quality (an example is depicted in Figure 1) and 50 low-quality fingerprint images (see Figure 2 for an example).

Minutiae have been manually marked in good quality images using a software tool. From the low-quality database, one image has been discarded, because no information could be marked with confidence. In the remaining 49 images, only very few minutiae have been clearly visible. For that reason, we inserted additional markings at locations where the orientation has been clearly discernible.

The comparisons consider the following four metrics. Firstly, the average deviation in the degrees which is for each image averaged over all pixels of the convex hull of the minutiae template and then averaged over all images of the set. Secondly, the percentage of pixels for which the reconstructed orientation deviates more the $15^\circ$ from the ground truth orientation (as in [9]). Thirdly, the root mean square deviation (RMSD) as defined in Eq. (1) of [10]. Fourthly, the average computational runtime per image for each method. All methods have been implemented in Java and the reconstructions have been computed on a notebook with 1.3 GHz Intel Core i5 CPU. The results are listed in Table 1.

### 5. CONCLUSION

To the knowledge of the authors this is the first direct comparison of OF reconstruction algorithms. We consider four algorithms from the literature including a number of modifications we propose. For evaluation we have used four metrics, the first three of which measure error, the fourth runtime. Overall, it turns out that while FJ is the most accurate method measured in all three error metrics, CZY1 is considerably faster, at the cost, however, of lower accuracy. Additional smoothing of FJ has not lead to further improvement of the accuracy. On the other hand, RSJ is least competitive, consistently displaying higher error measures and, coming with a long runtime.

### Acknowledgements

S. Huckemann and C. Gottschlich gratefully acknowledge the support of the Felix-Bernstein-Institute for Mathematical Statistics in the Biosciences and the Niedersachsen Vorab of the Volkswagen Foundation.

### 6. REFERENCES


Fig. 2. A low-quality example (a) from FOE [10] and its ground truth OF (second and third row of the first column). An overview over the OF reconstruction results (b-j). The second and fifth rows visualize the same reconstructed OFs in gray values between 0 and 179 for the respective orientation in degrees and white pixels denote background. The third and sixth row show the deviation of the reconstructed orientation from the ground truth. Here, white corresponds to $0^\circ$ and the intensity of red increases linearly as the deviation approaches $90^\circ$. 
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>FOE Set A Good</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. deviation</td>
<td>21.68</td>
<td>15.53</td>
<td>10.44</td>
<td>29.82</td>
<td>9.97</td>
<td>9.20</td>
<td>11.86</td>
<td>7.38</td>
<td>8.98</td>
</tr>
<tr>
<td>Percent dev. &gt; 15°</td>
<td>45.23%</td>
<td>34.59%</td>
<td>21.2%</td>
<td>60.23%</td>
<td>16.87%</td>
<td>16.22%</td>
<td>24.29%</td>
<td>10.88%</td>
<td>14.58%</td>
</tr>
<tr>
<td>RMSD</td>
<td>30.94</td>
<td>22.93</td>
<td>15.56</td>
<td>37.95</td>
<td>14.75</td>
<td>13.87</td>
<td>18.17</td>
<td>11.43</td>
<td>13.39</td>
</tr>
<tr>
<td>Avg. runtime in sec.</td>
<td>560.48</td>
<td>561.01</td>
<td>0.08</td>
<td>1.69</td>
<td>1.75</td>
<td>2.35</td>
<td>2.37</td>
<td>4.74</td>
<td>8.00</td>
</tr>
<tr>
<td>FOE Set A Bad</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. deviation</td>
<td>21.27</td>
<td>15.71</td>
<td>12.57</td>
<td>34.12</td>
<td>15.47</td>
<td>10.72</td>
<td>11.71</td>
<td>8.37</td>
<td>8.48</td>
</tr>
<tr>
<td>Percent dev. &gt; 15°</td>
<td>43.05%</td>
<td>34.38%</td>
<td>27.28%</td>
<td>68.36%</td>
<td>32.45%</td>
<td>21.04%</td>
<td>24.51%</td>
<td>13.08%</td>
<td>13.14%</td>
</tr>
<tr>
<td>RMSD</td>
<td>30.52</td>
<td>22.61</td>
<td>17.89</td>
<td>42.55</td>
<td>21.71</td>
<td>15.32</td>
<td>16.99</td>
<td>12.56</td>
<td>12.75</td>
</tr>
<tr>
<td>Avg. runtime in sec.</td>
<td>150.06</td>
<td>150.76</td>
<td>0.04</td>
<td>1.05</td>
<td>1.12</td>
<td>1.43</td>
<td>0.86</td>
<td>2.79</td>
<td>5.21</td>
</tr>
</tbody>
</table>

Table 1. Comparison of orientation field reconstruction methods described in Section 3 using the performance metrics and benchmark detailed in Section 4.


