Fingerprint Orientation Modeling using Symmetric Filters

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Abstract

Accurate fingerprint orientation is a prerequisite in fingerprint based recognition system. This paper proposes an algorithm for modeling the fingerprint orientation field by using a model based algorithm based on the weighted Legendre basis. Weights required in the modeling are obtained by using symmetric filters, such that: i) high weights should be assigned to the areas near singular points; ii) areas having uniform ridge-valley flow should be given high weights; and iii) areas containing bad quality due to dry/ wet fingerprints, scars, bruises or sensor condition should be given low weights. These conditions ensure accurate reconstruction of fingerprint orientation field for bad quality areas while preserving the true orientation field near singular points. The proposed algorithm has been evaluated on a publicly available database, FVC2004 DB1A. Experimental results reveal that it has better orientation field estimation compared to the various state of the art algorithms.

1. Introduction

Data protection or security is essential in recent years due to accessibility of large digital data and cheap hardware. Keys or passwords based security is not of much use as these can be easily forgotten, lost or stolen. Use of biometrics is a viable option for personal authentication, which uses individual characteristics for recognition. Fingerprint which is defined as an oriented texture pattern of ridges and valleys on the fingertip, is considered to be a highly useful biometric trait. It is extensively used in commercial applications, forensics and even in courts as a legal proof because it possesses the following properties: easily collectible, universality, uniqueness, user-friendly, permanence and acceptability [7]. But recognition of poor quality fingerprint recognition is still a challenging task. Poor quality fingerprints can be generated due to: (i) presence of dirt or latent print on sensor; (ii) wet, dry, dirty, greasy or wounded finger; (iii) finger contain scars or creases; and (iv) smoothened ridge-valley structure due to age or occupation.

Fingerprint image enhancement, fingerprint matching, singular point detection, fingerprint classification and fingerprint indexing are the main research question in designing a fingerprint based recognition system. All these require the accurate orientation field estimation, especially near the bad quality areas [13]. Thus, research in the direction of accurate fingerprint orientation estimation is continuously evolving. This has motivated us to propose an algorithm which can accurately estimate the orientation field, even in the case of bad quality fingerprints.

Orientation field can be estimated by using local methods like filter-bank based algorithm [9] and gradient-based algorithm [16]. Since there is nearly a constant ridge-valley flow in a local area of a fingerprint except for the areas near singular points, orientation field at each pixel can be estimated by using its local neighborhood. Local methods are based on this phenomenon and hence, its orientation field estimates are not much accurate near singular points. In filter-bank based algorithm [9], orientation field at each pixel is estimated by using several filters oriented in different directions. Similarly in gradient based algorithm [16], it is given by the averaging of squared gradients inside a local neighborhood. Orientation field estimates obtained by using local methods can be easily affected by the bad quality fingerprints. Low pass filtering can be used to somewhat reduce the noise, but it is found to be ineffective if local neighborhoods do not provide sufficient ridge flow information due to bad quality.

In a fingerprint, orientation field is expected to be smooth except in some areas near singular points. Thus, global structure can be used to model the orientation field using which orientation field near bad quality areas can be accurately interpolated. Several algorithms are proposed in the literature which use singular points for an accurate fingerprint orientation field modeling [5]. Since singular point detection is a challenging problem in bad quality fingerprints, such algorithms are usually avoided for fingerprint orientation modeling. Problem of fingerprint orientation modeling

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can also be formulated as a data fitting problem which does not require any prior knowledge of singular points. In such a scenario, orientation field obtained from local methods, are fitted by using some well defined basis functions. The parameters required for data fitting are obtained by using optimization algorithms. Basis functions and the modeling parameters are used to reconstruct the orientation field. Some examples of data fitting based orientation field modeling algorithms are polynomial fitting [21] and FOMFE [20] which use polynomial and trigonometric basis function respectively. Such algorithms cannot accurately model the orientation field in the areas consisting of bad quality or the areas near the singular points. It is observed that in these algorithms all the orientation field estimates are given equal weight or importance during modeling. But more accurate orientation field modeling can be achieved if some areas like the one having uniform flow should be given more weights during modeling compared to the one consisting of bad quality. Using this, weighted orientation field modeling algorithms are proposed. Algorithm [15] uses the Legendre basis along-with weighted modeling. It assigns a weight of one for foreground pixels (i.e., pixels belonging to the fingerprint area) while zero for background pixels. It shows better performance than other data fitting algorithms. But its modeled orientation field in the areas consisting of bad quality or singular points is spurious. Algorithms [19] and [17] assign the weights based on uniform and linear ridge-valley flow. It gives spurious modeled orientation field estimates for the areas near singular points because low weights are assigned to these areas during modeling. In contrast, the weights are given based on the singular points in [11]. It has been observed that: (i) spurious singular points can be generated due to bad quality; and (ii) singular points are absent in some fingerprints like the fingerprints consisting of arch pattern. In such cases, orientation field can be spuriously modeled by using algorithm [11].

In this paper, a weighted orientation field modeling algorithm is proposed where weights are assigned based on fingerprint quality. The proposed fingerprint quality estimation algorithm assigns low weights to the areas of bad quality while higher weights in the areas consisting of uniform linear flow. In addition, it assigns large weights to the areas near singular points. This paper is organized as follows. The next section presents the proposed weighted fingerprint orientation field modeling algorithm. Experimental results are discussed in Section 3. It is followed by the discussions. Conclusions are given in the last section.

2. Proposed Algorithm

This section consists of three stages. In the first stage, orientation field is estimated by using local methods. The fingerprint quality is proposed in the next stage. Weighted orientation field modeling is described in the last stage.

2.1. Orientation field estimation

Orientation field at each pixel of the given fingerprint image, I, is extracted by using the algorithm [8]. It is explained below for the sake of completeness in this section. In fingerprints, foreground pixels have high variance while background pixels have low variance. Thus, foreground mask, F_I, is obtained by using variance in a block. It consists of 1 and 0 which represent the foreground and background pixels respectively. Background pixels are set to 255 in I and it is subsequently normalized to a specific mean and variance. Orientation of each pixel in the normalized image is estimated by using least mean square estimation. It requires the gradients of the normalized image which are obtained by using Sobel operator. Let G_x and G_y represent the gradients in x and y direction respectively. Then, orientation field, θ, for each block centered at pixel (i, j) is obtained by using:

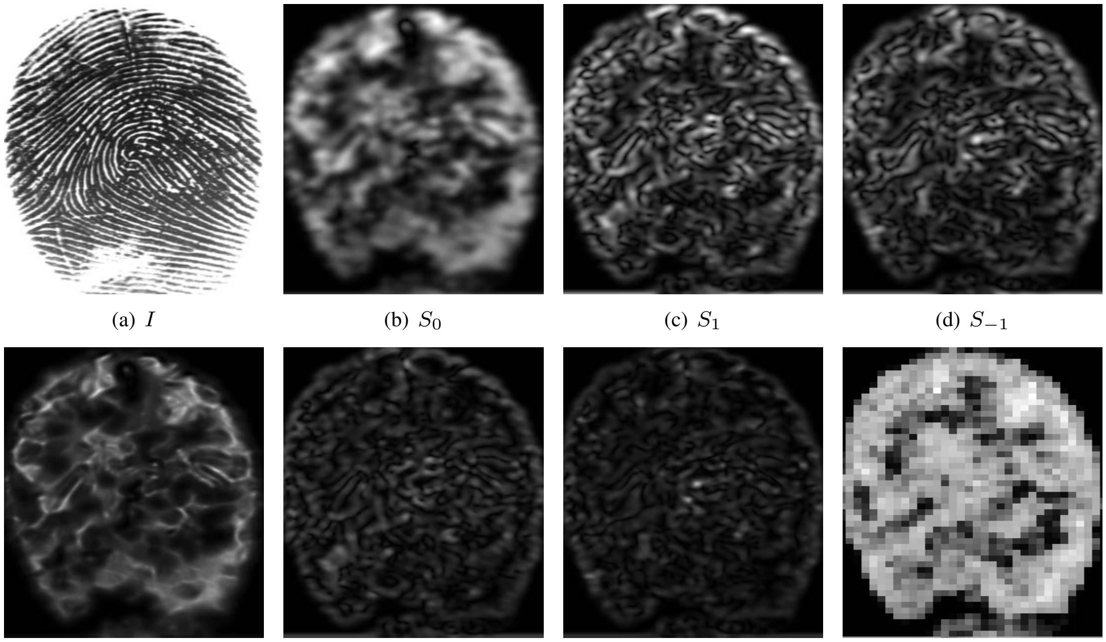
$$\theta(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{\sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}}\sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2G_x(i,j)G_y(i,j)}{\sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}}\sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} (G_x^2(i,j) - G_y^2 i,j))}\right) \tag{1}$$

where w is the block size. It may be spurious due to noise or smudged ridge-valley structure, thus it is smoothened by using a low pass Gaussian filter. Publicly available Matlab codes [10] are used to extract the orientation field.

2.2. Quality estimation

In this section, the quality of a fingerprint is estimated. Since it will be used as weights for orientation field modeling, it should be defined to cater the requirements of effective orientation field modeling. Thus, it should contain: (i) high values for the areas consisting of uniform ridge-valley flow and are near to singular points; (ii) high values for the areas containing linear and uniform ridge-valley flow; and (iii) low values for dry and wet fingerprint areas. There are various algorithms for fingerprint quality estimation [2]. Some of these algorithms measure the strength of orientation field like Gabor filter based approach, orientation certainty level and reliability. They have low values at areas near singular points due to high curvature and thus, they are not used. Similarly, pixel based fingerprint quality estimation algorithms measure the clarity between the ridge-valley structure like mean, variance, local contrast and local clarity. They perform poorly in the areas containing high curvature and thus, avoided. In this paper, quality of the given fingerprint is estimated by using symmetric filters which were initially designed for singular point detection. The motivation behind the usage of symmetric filters is that different parabolic symmetric filters can be used to measure the consistency of ridge-valley flow near singular points [4].

In essence, a symmetric filter work in the following way. It represents a specific shape pattern which is convolved



(a) I (b) S_0 (c) S_1 (d) S_{-1}

(e) $\hat{S}_0$ (f) $\hat{S}_1$ (g) $\hat{S}_{-1}$ (h) Q

Figure 1. Example of Symmetric Filter based Fingerprint Quality

with the orientation tensor (holding the edge information) of an image to obtain the filter response. Filter response determines the similarity between the local orientations and a specific pattern represented by the symmetric filter. The main advantage of these responses is that they are scale and rotation invariant in a local neighborhood. Based on domain knowledge, a particular pattern corresponding to a symmetric filter is used.

For fingerprints, squared orientation field, $\hat{\theta}$ (i.e., $2 \times \theta$), is converted into the complex field, to obtain the orientation tensor, z. That is,

$$z = \cos(\hat{\theta}) + i\sin(\hat{\theta}) \tag{2}$$

z is decomposed into various symmetric descriptors each of which measures the consistency of ridge-valley flow for a specific type of pattern. Let S_j represents the symmetric descriptor of j^{th} order which is obtained by convolving the z with the symmetric filter of order j. Let h_j represents the symmetric filter for order j which is given by

$$h_j(x, y) = \begin{cases} (x + iy)^j \cdot g(x, y) & if\ j \geq 0 \\ (x - iy)^{|j|} \cdot g(x, y) & otherwise \end{cases} \tag{3}$$

where (x, y) represent a pixel location while g obeys 2D Gaussian distribution with standard deviation σ. Symmetric descriptor S_j is given by

$$S_j = \frac{\langle z, h_j \rangle}{\langle |z|, h_0 \rangle} \tag{4}$$

Besides convolution, normalization is also performed in this equation in order to restrict the value of S_j between 0 and 1. A fingerprint image contains uniform linear flow, i.e., linear symmetry which can be represented by using a symmetry filter of order 0 (i.e., h_0). Similarly, its area near ridge bifurcation, ridge ending, core points and delta points can be represented by using parabolic symmetric filters of order 1 or -1 (i.e. h_1 or h_{-1}) [6]. Hence, S_0, S_1 and S_{-1} are used for fingerprint quality estimation, which are calculated by using the Equation (3) and Equation (4) for order j = 0, 1 and -1 respectively. Even though these symmetric descriptors measures the uniformity irrespective of the curvature, these perform poorly for bad quality fingerprints. It has been observed that a fingerprint area has a specific type of pattern represented by h_0, h_1 or h_{-1}, i.e., it has large value for a particular symmetric descriptor. If large values for different symmetric descriptors are present in an area, then it indicates the area contains noise or blur. Thus, symmetric descriptors are modified such that large values of symmetric descriptors are reduced in bad quality areas by using

$$\hat{S}_j = S_j \prod_{k \in J \setminus j} (1 - |S_k|) \cdot F_I \tag{5}$$

where $\hat{S}_j$ is the modified symmetric descriptor for order j; k refers to all the order values except order j and J refers to all the order values. Equation (5) is multiplied with foreground mask, F_I, to remove the background pixels. It leverages the intuition that if different symmetric descriptors have large values, then, these values should be tremendously decreased to indicate the existence of bad quality. Modified symmetric descriptors are normalized by using min-max normalization and subsequently, consolidated to estimate the pixel-wise fingerprint quality, Q_1, by using

$$Q_1 = \hat{S}_{-1} + \hat{S}_0 + \hat{S}_1 \tag{6}$$

Q_1 may contain small noises which are removed by estimating the block-wise quality estimates. It is divided into non-overlapping blocks of block-size, B. Quality of a block is determined by summing the quality of its pixels. Since pixel-wise quality is required for orientation field modeling, quality of a block is replicated at each of its pixels. Let Q denote the obtained pixel-wise quality estimate. Steps involved in fingerprint quality estimation are shown in Algorithm 1. An example of fingerprint quality estimation by using the proposed algorithm is shown in Figure 1. It is apparent from Figure 1(h) that the proposed fingerprint algorithm assigns low weights to the bad quality areas arise due to creases, wet and dry fingerprint while high weights are assigned to the areas containing uniform ridge-valley flow, irrespective of the curvature.

Algorithm 1 FingerprintQuality(θ, F_I)

Require: θ and F_I which store the orientation field and foreground mask.

Ensure: Q contains the fingerprint quality.

1: Find orientation tensor, z by using Equation (2).
2: Symmetric filters h_0, h_1 and h_{-1} are formed by using Equation (3), for n = 0,1 and -1.
3: Apply Equation (4) to obtain symmetric descriptors, S_0, S_1 and S_{-1} by using h_0, h_1 and h_{-1} respectively.
4: **for** each pixel (x, y) in I **do**
5: Obtain modified symmetric descriptors at each pixel ($\hat{S}_0(x, y)$, $\hat{S}_1(x, y)$, $\hat{S}_{-1}(x, y)$) using Equation (5).
6: $Q_1(x, y) = \hat{S}_0(x, y) + \hat{S}_1(x, y) + \hat{S}_{-1}(x, y)$
7: **end for**
8: Divide Q_1 into non overlapping blocks of block-size, B. Quality of a block is estimated by adding the values of Q_1 lying inside the block. It is replicated to each of its pixel to obtain the pixel-wise quality estimates, Q.
9: **return** (Q)

2.3. Quality based Orientation Field Modeling

The proposed orientation field modeling consists of following features:

1. Basis functions can be defined in various ways like FOMFE [20] and polynomial fitting [21]. But, Legendre polynomials are used to define the basis functions in this paper because: (i) Legendre's polynomial based model algorithm has shown better perform than other model based algorithms [15]; (ii) Orthogonal nature of Legendre's polynomial can improve the stability of the optimization algorithm by guaranteeing small residual error; and (iii) Higher order Legendre basis can be easily generated by using lower order Legendre basis, which helps to reduce the time computation.

2. In order to eliminate the problem of orientation discontinuity at zero and π, squared orientation field, $\hat{\theta}$, is used for orientation modeling instead of θ.

3. Weighted least square algorithm is used for weighted orientation field modeling. It preserves orientation field in areas containing high weights while it reconstructs orientation field in areas containing low weights.

Let g_{sin} and g_{cos} represent the sine and cosine components of $\hat{\theta}$ respectively. These can be decomposed at a pixel location (x, y) by using the Legendre polynomial basis functions of order n. That is,

$$g_{cos}(x, y) = cos\left(\hat{\theta}(x, y)\right) \approx \sum_{i=0}^{n}\sum_{j=0}^{n-i} a_{i,j}\phi_{i,j}(x, y) \tag{7}$$

$$g_{sin}(x, y) = sin\left(\hat{\theta}(x, y)\right) \approx \sum_{i=0}^{n}\sum_{j=0}^{n-i} b_{i,j}\phi_{i,j}(x, y) \tag{8}$$

Legendre polynomial basis functions are stored in ϕ while $a_{i,j}$ and $b_{i,j}$ are the coefficients of $g_{cos}(x, y)$ and $g_{sin}(x, y)$ respectively. Equations (7) and (8) can be written in matrix form as:

$$g_{cos}(x, y) = \phi^T(x, y)\, A \tag{9}$$

$$g_{sin}(x, y) = \phi^T(x, y)\, B \tag{10}$$

such that

$$A = [a_{0,0}\;\; a_{0,1}\;\; a_{1,0} \cdots\; a_{n,0}]^T \tag{11}$$

$$B = [b_{0,0}\;\; b_{0,1}\;\; b_{1,0} \cdots\; b_{n,0}]^T \tag{12}$$

$$\phi(x, y) = [\phi_{0,0}(x, y)\;\; \phi_{0,1}(x, y) \cdots\; \phi_{n,0}(x, y)]^T \tag{13}$$

Each $\phi_{i,j}$ is obtained by using recurrence relationship and variable separability which is given by:

$$(n+1)\phi_{n+1}(x) = (2n+1) \times \phi_n(x) - n \times \phi_{n-1}(x), \tag{14}$$

$$\phi_{i,j}(x, y) = \phi_i(x) \times \phi_j(y) \tag{15}$$

Parameters A and B can be estimated by

$$\hat{A} = \arg_A \min \|(\mathbf{W}(\mathbf{G_{cos}} - \Phi A)\|^2 \tag{16}$$

$$\hat{B} = \arg_B \min \|(\mathbf{W}(\mathbf{G_{sin}} - \Phi B)\|^2 \tag{17}$$

where $\|.\|$ represents the norm while $\hat{A}$ and $\hat{B}$ are the estimated A and B respectively such that the sum of squared residuals is minimized. Also, $\mathbf{G_{cos}}$, $\mathbf{G_{sin}}$, $\mathbf{W}$ and $\mathbf{\Phi}$ are the 1-D matrix representation of $g_{cos}(x,y)$, $g_{sin}(x,y)$, $Q(x,y)$ and $\phi(x,y)$ at each location (x,y) in $\hat{\theta}$ respectively. That is,

$$\mathbf{G_{cos}} = \left[g_{cos}(0,0) \;\; g_{cos}(0,1) \cdots \;\; g_{cos}(p,q)\right]^T \tag{18}$$

$$\mathbf{G_{sin}} = \left[g_{sin}(0,0) \;\; g_{sin}(0,1) \cdots \;\; g_{sin}(p,q)\right]^T \tag{19}$$

$$\mathbf{W} = \left[Q(0,0) \;\; Q(0,1) \cdots \;\; Q(p,q)\right]^T \tag{20}$$

$$\mathbf{\Phi} = \left[\phi(0,0)^T \;\; \phi(0,1)^T \cdots \;\; \phi(p,q)^T\right]^T \tag{21}$$

If size of $\hat{\theta}$ is given by $p \times q$ then, Equation (16) and Equation (17) represent $(2 \times p \times q)$ equations and $(\frac{n(n+1)}{2})$ unknown parameters. Such an overdetermined system of equations is solved to obtain $\hat{A}$ and $\hat{B}$ by using weighted least square. That is:

$$\hat{A} = \left(\mathbf{\Phi}^T \bar{\mathbf{W}} \mathbf{\Phi}\right)^{-1} \mathbf{\Phi}^T \bar{\mathbf{W}} \mathbf{G_{cos}} \tag{22}$$

$$\hat{B} = \left(\mathbf{\Phi}^T \bar{\mathbf{W}} \mathbf{\Phi}\right)^{-1} \mathbf{\Phi}^T \bar{\mathbf{W}} \mathbf{G_{sin}} \tag{23}$$

$\bar{\mathbf{W}}$ is the diagonal weight matrix which is given by:

$$\bar{\mathbf{W}} = diag\left(Q(0,0), Q(0,1), \cdots \; Q(p,q)\right) \tag{24}$$

Modeled orientation field, $\bar{\theta}$, is obtained by using:

$$\bar{\theta}(x,y) = \frac{1}{2}\tan^{-1}\frac{\left(\phi^T(x,y)\,\hat{B}\right)}{\left(\phi^T(x,y)\,\hat{A}\right)} \tag{25}$$

Examples of the proposed orientation field modeling are shown in Figure 2.

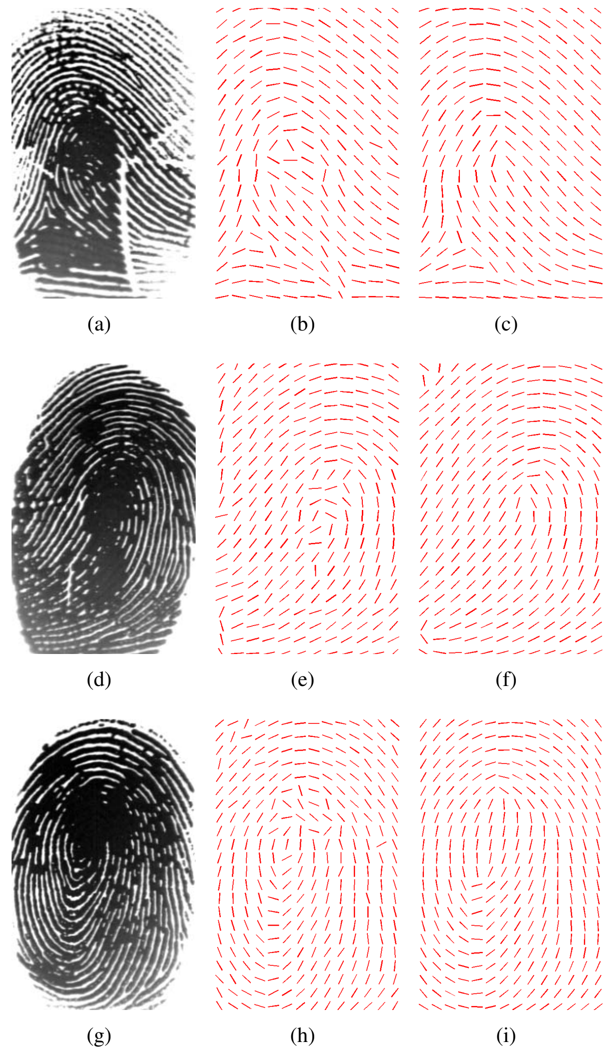


Figure 2. Example of Modeled Orientation Field. Fingerprints are shown in first column while corresponding actual and modeled orientation field are shown in second and third columns respectively.

3. Experimental Results

Accurate fingerprint modeling requires that genuine orientation field near singular points should be preserved while spurious orientation field near the bad quality areas should be smoothened out otherwise it can generate spurious singular points. The performance of the proposed quality based orientation field modeling algorithm has been analyzed in this section by using genuine singular points detection. Publicly available database FVC2004 DB1A [1] has been used for analysis which contains 800 fingerprint images, each of size 640×480 pixels. These images are acquired under uncontrolled environment and thus contains bad quality images [12]. Some fingerprint areas which are close to the fingerprint boundaries are considered as background and if a singular point lies in such an area, then it is not considered during evaluation. Singular points present in the database images are manually annotated and total 966 core points and 532 delta points are considered for performance evaluation. All the algorithms required during the experimentation are implemented in MATLAB 7.2 and simulated on a desktop computer having Intel Pentium 8 processor, 2.8 GHz with 4GB RAM.

Parameters used in the orientation field estimation are set by using [10], [8] and [18]. Likewise, parameters for constructing the symmetric filters are given by [14] where symmetric filters are used for singular point detection. Blocksize, B, which removes the local noises in fingerprint quality is set to be 16. Only one parameter is used in weighted orientation modeling, viz., order n of Legendre polynomial basis. Experimentally, it is found out that n equals to 6 gives the best possible orientation field modeling.

In this section, singular points are extracted from the orientation field by using the Poincare index method [3]. Following metrics are used for performance evaluation of singular point detection:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{26}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{27}$$

$$\text{F-measure} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{28}$$

where TP, FN and FP denote the number of true positive, false negative and false positive respectively. Accurate orientation field modeling indicated by genuine singular point detection, requires high values of Precision, Recall and F-measure. A singular point can be regarded as true positive if the Euclidean distance between the detected and annotated singular point is less than 24 pixels. Another metric known as localization error is also used for performance evaluation. The localization error of a singular point is given by the Euclidean distance between its detected location and its manually annotated location.

In Table 1, various algorithms are compared with the proposed algorithm. Parameter values (like orders) of these algorithms are set as proposed by the respective authors of the algorithm. In addition, the performance is also analyzed when the proposed quality and weighted modeling are used along-with basis functions given in [11] and [20]. It can be inferred from Table 1 that:

	Algorithm^{+}	TP	Precision (%)	Recall (%)	F-measure (%)	Error$^{\#}$
Delta	[20]	365	77.49	68.61	72.78	22.14
	[17]	368	80.88	69.17	74.57	20.68
	Q + [20]*	371	83.56	69.74	76.03	18.23
	[11]	302	70.89	56.77	63.05	11.91
	Q + [11]*	325	76.83	61.09	68.06	11.75
	[15]	372	80.69	69.92	74.92	20.82
	Proposed	*390*	*87.84*	*73.31*	*79.92*	*10.23*
Core	[20]	900	89.29	93.17	91.19	28.32
	[17]	918	91.16	95.03	93.05	25.61
	Q + [20]*	927	92.33	95.96	94.11	21.75
	[11]	882	86.81	91.30	89.00	16.24
	Q + [11]*	902	90.74	93.37	92.04	16.06
	[15]	913	90.76	94.51	92.60	25.89
	Proposed	*932*	*93.86*	*96.48*	*95.15*	*14.73*

*: It uses proposed quality and weighted modeling but basis functions are chosen from the paper.
$^{+}$: Only orientation field modeling algorithm.
$^{\#}$: Mean of localization errors.

Table 1. Comparative Results of Singular Point Detection

1. Performance of a model based algorithm can be improved if it uses weighted orientation field modeling instead of orientation field modeling. Reason behind this is that most of the useless orientation field estimates (like the ones derived from background pixels) can be ignored.

2. Algorithms [15] and [17] assign equal and low weights respectively in the area near singular points. Also, they do not appropriately handle the bad quality areas. Due to these reasons, obtained modeled orientation field near singular points are spurious. Singular points extracted from such spurious orientation points are largely deviated from the actual locations which increases the localization error. Sometimes genuine singular points are missed and spurious singular points are generated due to spurious orientation field which decreases the Precision, Recall and F-measure.

3. Algorithm [11] assigns large weights to the area near singular points, thus it has a low localization error. But it does not consider: i) the bad quality areas which often look like singular points; and ii) uniform linear ridge-valley flow. Thus, it generates a large number of spurious singular points and misses a large number of genuine singular points which decrease the TN and increase the FP, which in turn, decreases the Precision, Recall and F-measure.

4. If the proposed quality is used as weights, then the performance of available model based algorithms increases because: (i) FN are decreased while TP are increased by assigning high weights to the areas near singular points; and (ii) FP are decreased by assigning low weights to the bad quality areas.

5. It has been observed that there are a large number of bad quality fingerprints in the database where the core points are occluded by wet fingerprint areas. Orientation field near such core points are reconstructed and such core points have high localization errors. Also the performance of the proposed algorithm for delta point extraction is best amongst the available algorithms. But some genuine delta points lie near fingerprint boundary are missed because they cannot be accurately modeled by the proposed algorithm.

4. Discussion

This paper has successfully designed an orientation field modeling algorithm which performs better than other existing algorithms, even for bad quality fingerprint. We have not experimented with other orientation field estimation algorithms and better performance can be expected if better orientation field estimates algorithms are used. By including the proposed quality parameter, an extra time of 89ms is added, but it is negligible compared to the time taken in orientation field modeling which is 2416ms.

The proposed algorithm and the algorithm [15] are different in the following ways: (i) the proposed algorithm uses the fingerprint quality while algorithm [15] uses foreground pixels as weights for orientation field modeling; and (ii) Levenberg Marquard Algorithm (LMA) is used to minimize the cost function in algorithm [15] while weighted least square based optimization is used in this paper. LMA is an iterative process and thus, more time consuming compared to weighted least square.

5. Conclusion

One of the main requirements in designing a fingerprint based recognition system, is the accurate extraction of fingerprint orientation. Unfortunately, bad quality fingerprints generated due to due to dry/ wet fingerprints, scars, bruises or sensor condition can generate spurious orientation field. In this paper, a fingerprint orientation field modeling algorithm has been proposed to reconstruct the orientation field near bad quality areas while preserving the genuine orientation field near singular points. It has used model based algorithm based on the weighted Legendre basis. Weights have been obtained by using symmetric filters, such that: i) areas near singular points have high weights; ii) areas belonging to uniform ridge-valley flow contain high weights; and iii) bad quality areas have low weights.

The proposed algorithm has been evaluated on a publicly available database, FVC2004 DB1A. Experimental results have illustrated that performance of a model based fingerprint orientation modeling algorithm can be improved if the proposed symmetric filter based quality estimation is used during modeling. In addition, it has demonstrated that the proposed orientation field modeling algorithm has better performance than the other state of the art algorithms.

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