Active Fingerprint Ridge Orientation Models

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Abstract. This paper proposes a statistical model for fingerprint ridge orientations. The active fingerprint ridge orientation model (AFROM) iteratively deforms to fit the orientation field (OF) of a fingerprint. The OFs are constrained by the AFROM to vary only in ways according to a training set. The main application of the method is the OF estimation in noisy fingerprints as well as the interpolation and extrapolation of larger OF parts. Fingerprint OFs are represented by Legendre Polynomials. The method does not depend on any pre-alignment or registration of the input image itself. The training can be done fully automatic without any user interaction. We show that the model is able to extract the significant appearance elements of fingerprint flow patterns even from noisy training images. Furthermore, our method does not depend on any other computed data, except a segmentation. We evaluated both, the generalisation as well as the prediction capability of the proposed method. These evaluations assess our method very good results.

1 Introduction

Automatic Fingerprint Identification Systems (AFIS) have evolved to a mature technique and are becoming part of the daily lives of millions of people all over the world. For example, in many countries fingerprints are taken as part of the visa application process. Therefore, in the recent years we observe a step into a new dimension with respect to the size and complexity of automatic fingerprint identification systems. Large attention has been paid to the emerging problems, but still there is an ever-increasing need for better recognition rates. The latter is especially true for fingerprint images of poor quality.

The attractiveness of fingerprints results from their uniqueness which does not change through the life of individuals [10]. Three types of characteristic features [7] can be extracted from a fingerprint image: a) patterns, which are the macro details of a fingerprint such as ridge flow and pattern type. b) minutiae, which are points where ridges bifurcate or end. c) pores, edge contours, incipient ridges, breaks, creases and other permanent details.

The extraction of the key features (fingerprint patterns, minutiae) is highly depending on the correct estimation of local ridge orientation. Ridge orientation is inevitably used for detecting, describing and matching fingerprint features such as minutiae and singular points (SPs). For minutiae detection, special filtering schema (see references in [7]) are available to enhance fingerprint images in order to extract the last bit of information available in the image. Note that the use of the mentioned filtering methods can only be successful if the correct ridge orientation is available.

Therefore, large efforts are made in order to extract reliable orientation data from fingerprints. Many methods for ridge orientation estimation exist in the literature (see [7]). The described methods proceed locally, and extract the orientation in a given area. Typically, this is done by estimating the gradients in the considered area. Unfortunately, determination of ridge orientation becomes more difficult when image quality is low (typically caused by noise, smudges, scars, weat or dry fingers, etc.). Thus even the 'best' orientation estimation algorithm will fail in regions of low image quality. The classic solution to solve this problem, is to smooth the ridge orientation. Such filtering methods are mostly based around an approach described by Witkin and Kass in [8]. This method splits orientation into vectorial parts (x-part, y-part) and then smooths this parts using low pass filtering schema. Note that this method is identical to the method of local orientation by tensor smoothing [2]. A representative example of a low pass filtering scheme is described by Bazen and Gerez in [1]. It is noteworthy to mention, that using such filtering methods, only small regions can be re-estimated successfully.

1.1 Related Work

The limitations of the above mentioned filtering schema gave rise to more sophisticated, model-based methods. Model-based approaches attempt to re-estimate OFs of larger areas in the image.

Early attempts of fingerprint ridge orientation modelling are described by Sherlock et al. [12] who model the orientation using a so-called zero-pole model. This orientation model is far too simple and fails describing the ridge orientation accurately. Vizcaya and Gerhardt improve on this model in [13] by using a piecewise linear model around the SP. This model is applied for synthesis of fingerprints as described in [7].

A combination method is described by Zhou and Gu in [16,17]. These methods first describe the global orientation field using power series and than model SPs locally. Unfortunately, the algorithm is difficult to apply in practice, since combining the two parts of the model involves heuristics. Furthermore, the algorithm requires reliable detection of SPs.

In [9], Li et al. model the orientation of fingerprints using higher order phase portraits. Therefore, the method divides the fingerprint into several predefined regions and approximates them using piecewise linear phase portraits. In a further step this method computes a global model using the piecewise linear phase portraits. Similar problems as described above apply also to this algorithm, namely the required separation of fingerprints into predefined regions and the robust detection of SPs.

Wang et al. [14] present a OF model based on trigonometric polynomials. Their approach (coined FOMFE) does not require the detection of SPs. The application includes orientation interpolation, SP detection and database indexing based on the model parameters. For OF smoothing, we [11] found that this method does not perform significantly better in comparison to classical low pass filtering schema.

Another method is described in [11], where we propose the use of Legendre Polynomials for modelling fingerprint OFs. We argue that SPs yield discontinuities in the OF which are difficult to model using polynomials. Instead we propose to use a fractional term, where the numerator and denominator parts are computed from the orientation (vectorial x-part, y-part). A non-linear optimization scheme enables this fractional function to approximate high curvature areas (especially SPs) without the necessity to model discontinuities. This is achieved by exploiting the zero-poles of the polynomials for modelling SPs and enables the method to perform better than other methods.

Very recently, Huckemann et al. [6] proposed a global OF model-based on quadratic differentials. This model can approximate fingerprint OFs using only five coefficients. These coefficients are geometrically interpretable and have a clear meaning. One drawback of this method is that it can not model every fingerprint type. Furthermore, the model is clearly not 'flexible' enough for a precise approximation of fingerprint OFs.

1.2 Prior Knowledge within Fingerprint Orientation Models

All the above mentioned fingerprint OF models do not contain the possibility of adding prior knowledge to aid the process of orientation estimation. The nomenclature of the term prior knowledge in this context implies that the model 'knows' patterns of valid fingerprints. Prior knowledge of valid fingerprint patterns can be used to provide tolerance to noisy or missing data. There are two main characteristics which the model should possess. First, the model should be general, meaning it should be capable of generating any plausible fingerprint pattern. Second, and crucially, it should be specific, which means the model should only be capable of generating 'naturally occurring' fingerprint patterns.

Typical examples of active models in literature are active shape models (ASM) used for modelling shape variations and active appearance models (AAM) for matching a statistical model of object shape and appearance to a new image. These models are built during a training phase. The latter method is widely used for matching and tracking faces and for medical image interpretation. For a more thorough overview see [3].

2 Training the Model

We use commercial fingerprint software from Siemens (Siemens IT Solutions and Services, Biometrics Center) for local OF estimation and for the segmentation of the image into foreground/background pixels. Note that no other processing, i.e. registration or alignment has been employed. For the training phase, the raw OF is smoothed using the method described in [11], this step is essential as it is necessary to estimate the OF also in the corners of the image (background).

2.1 Representation of Fingerprint Flow Patterns

For the representation of fingerprints OFs, we use 12^{th} order Legendre Polynomials as described in [11]. Alternatively, one could also use the parametric OF representation as described in [14] by Wang et al. In the following, we give a short overview of the used OF approximation method. Let $2O(x, y)$ be the doubled orientation and $\Phi(\mathbf{x}) = [\phi_0(\mathbf{x}) \dots \phi_n(\mathbf{x})]$ the row vector containing the set of basis functions $\phi(\mathbf{x})$ evaluated for a given coordinate $\mathbf{x} = (x, y)$. The system matrix is given as $\mathbf{V}$ and consists of the row vectors $\Phi(\mathbf{x})$. $\mathbf{f_x}$ and $\mathbf{f_y}$ contain the vectorial orientation data (computed using sine/cosine function from $2O(x, y)$). Then one can compute the parameter vector $\mathbf{c} = [\mathbf{a}, \mathbf{b}]$ for the vectorial approximation as described in the following:

$$\mathbf{a} = \mathbf{V_w^+ W f_y} \qquad \qquad \mathbf{b} = \mathbf{V_w^+ W f_x} \tag{1}$$

Where $\mathbf{V_w^+} = (\mathbf{V}^T\mathbf{W}\mathbf{V})^{-1}\mathbf{V}^T$ is the pseudo-inverse of the system matrix $\mathbf{V}$. The diagonal weighting matrix $\mathbf{W}$ is computed using fingerprint segmentation, where the diagonal elements are $\omega = 0$ for background and $\omega = 1$ for foreground pixels. For further details regarding the construction of the system matrix $\mathbf{V}$ we refer the reader to [11].

2.2 Computing a Subspace

Suppose now we have s sets of parameters $\mathbf{c}_i = [\mathbf{a}_i, \mathbf{b}_i]$ which were generated from s fingerprints as described above. These vectors form a distribution in the n dimensional space. If one can model this distribution, one can generate new examples similar to those in the original training set. Furthermore, one can decide whether a given OF is a plausible fingerprint flow patterns. We apply Principal Component Analysis (PCA) to the set of parameters in order to find a linear subspace where realistic fingerprints 'reside'. Therefore, we compute the mean $\bar{\mathbf{c}}$ and the covariance $\mathbf{S}$ of the data, followed by the eigenvectors $\mathbf{e} = [e_1, e_2, \dots, e_t]$ and the corresponding eigenvalues $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \dots, \lambda_t]$ of $\mathbf{S}$ (sorted largest first). Let Ω be the space of all possible parameters and Ψ the linear subspace spanned by the PCA. Then we can project parameters from Ω to Ψ using the linear projection φ:

$$\mathbf{d}_i = \varphi(\mathbf{c}_i) \qquad = \mathbf{e}^T(\mathbf{c}_i - \bar{\mathbf{c}}) \qquad \text{projection } \varphi \tag{2}$$

$$\mathbf{c}_i = \varphi^{-1}(\mathbf{d}_i) \qquad = \bar{\mathbf{c}}_i + \mathbf{e}\mathbf{d}_i \qquad \text{inverse projection } \varphi^{-1} \tag{3}$$

here $\mathbf{c}_i$ represents a point in the high dimensional space Ω and $\mathbf{d}_i$ the same point projected in to the linear subspace Ψ. The number of eigenvectors t to retain should be chosen so that the model represents a sufficiently large proportion of the total variance. Thus, the original high dimensional data can be approximated using a model with much fewer parameters. In Figure 1 the eigenvalue spectrum of 2000 fingerprint vectors (NIST4, f-prints database) is shown. Note that these fingerprints were not registered nor aligned in any other form. Only image cropping according to a segmentation has been performed.

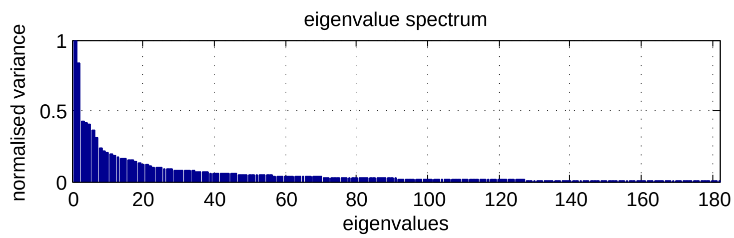


Fig. 1. Eigenvalue spectrum of 2000 fingerprint vectors (NIST4 f-prints database). Note how the first 40 eigenvalues correspond to more than 95% of the data's variance.

3 Fitting the Model to the Nearest Plausible Fingerprint Flow Pattern

In order to only generate examples similar to the training set, we have to choose a parameter $\mathbf{d} \in \Psi$. Therefore, we have to minimize the following cost function:

$$\underset{\mathbf{d}}{min} \quad \sum_{j=1}^{i} \omega_i \left[\sin\Big(M(\mathbf{x}_j) - O(\mathbf{x}_j)\Big)\right]^2 + \mu \left[\frac{1}{P(\mathbf{x}_j)} - P(\mathbf{x}_j)\right]^2 \tag{4}$$

The cost function compares the model's orientation estimation $M(\mathbf{x}_j)$ with the observed function value $O(\mathbf{x}_j)$ (obtained from local image gradients). We use the sin-function in order to resolve the discontinuity problem at zero and π. Then, one can compute $M(\mathbf{x}_j)$ as described in Equation 5:

$$M(\mathbf{x}_j) = \frac{1}{2} \arctan \frac{\Phi(\mathbf{x}_j)\mathbf{a}^T}{\Phi(\mathbf{x}_j)\mathbf{b}^T} \quad (5) \qquad P(\mathbf{x}_j) = (\Phi(\mathbf{x}_j)\mathbf{a}^T)^2 + (\Phi(\mathbf{x}_j)\mathbf{b}^T)^2 \quad (6)$$

Note that $\mathbf{a}$ and $\mathbf{b}$ can be computed by the inverse mapping $\mathbf{c} = [\mathbf{a}, \mathbf{b}] = \varphi^{-1}(\mathbf{d})$ The second term of Equation 4 is a penalty function which regularizes the orientation vector to unit length ($\sin^2 + \cos^2 = 1$). This regularization (given in Equation 6 is necessary since the the training was done exactly with this condition fulfilled. On the other hand, allowing a minor deviation from unit length provides tolerance to rotation and translation.

3.1 Optimization

The minimization of the cost function in Equation 4 is done by using the Levenberg-Marquard (LM) algorithm. Note that, as described above, each iteration of the LM uses the inverse mapping $\mathbf{c}_i = \varphi^{-1}(\mathbf{d}_i)$ in order to evaluate the cost function as given in Equation 4. The factor μ is set to $3 * 10^{-4}$ in all our experiments. The initial value $\mathbf{d_0}$ for the LM is set to the null vector. This corresponds to the mean OF ($\overline{\mathbf{c}}$). The LM algorithm stops when a minima is reached or when the number of iterations exceeds 40.

4 Evaluation

This section presents the experimental results. For training the model, we used the NIST4 special database [15]. This database contains 2000 fingerprints evenly distributed among the five Henry classes. The number of eigenmodes is limited to 80. For evaluation of the proposed method, we used the NIST4 s-prints (all 2000 images) and the FVC2006 2a [4] (all 1680 images) database.

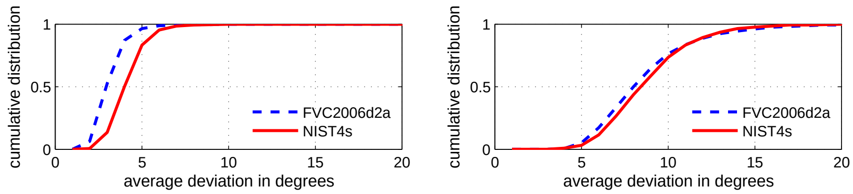
4.1 Generalisation Test

In this subsection we test how well the proposed model generalises to a given test database. Therefore the model is fitted to the raw (unsmoothed) OF of the given fingerprint. To measure the quality of the fit, we compute the absolute mean deviation between the ground truth OF and the fitted orientation field in degrees, where a error is only computed for foreground pixels. The ground truth OF is computed using the mentioned fingerprint software. The figures depicted in Figure 2(a) show cumulative distribution functions of the absolute mean deviation in degrees summarized over all images of the database. Most of the images show a mean deviation of smaller than five degrees. A large fraction of this error can be adhered to the block-wise processing of the commercial fingerprint matcher. Furthermore, we want to point out that the ground truth OF contains errors and thus a possible improvement using the proposed method is impossible to measure.

The reader should note that this evaluation procedure is exactly the same as described in [6]. The experiments and datasets are identical, but the authors of [6] deleted 20% of the images (due to missing SPs). In direct comparison our model generalises significantly better to fingerprints than the one proposed by Huckemann et al. [6]. We can report almost all of the images to have smaller than 10 degrees absolute mean deviation, in comparison [6] can only report 50%.

4.2 Prediction Test

The orientation interpolation capability of the proposed algorithm is tested in a simulated scenario where we remove 70% of the OF (see Figure 3). The OF remains in a rectangle with 40% area size, except a smaller rectangle with 10%



(a) *generalisation* (b) *prediction*

Fig. 2. Generalisation and Prediction Evaluation.

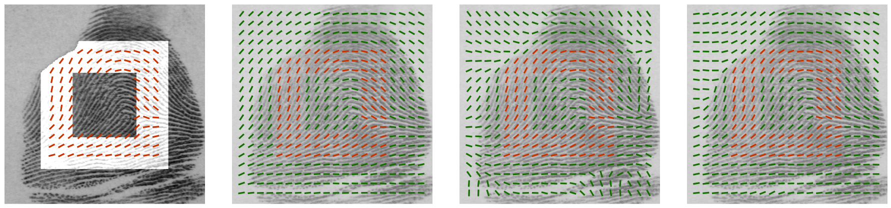
of the total image size in pixels. Both rectangles are centred in the middle of the image and exhibit the same aspect ratio as the image. Using this scenario, we tested the extrapolation as well as interpolation ability of the proposed algorithm. The figures are computed for the predicted OF only. Additionally, the background is removed from the input OF. This prediction evaluation is done using the same database configuration as mentioned above. It should be noted that not all predictions with a large absolute mean deviation are wrong in terms of plausibility.

The only comparable work with a significant large evaluated database is available from Hotz [5] (co-author of [6]). In his evaluation scenario the prediction was performed for only 5% occlusion (compared to 70% of our testing scenario). Unfortunately, this makes a possible comparison meaningless.

In Figure 6 one can see the translation and rotation invariance of the proposed method. Illustration 6(c) shows a 180 degree rotated image of a loop type fingerprint (the straight example is given in Figure 5). As can be seen, the model corrects the OF to a whorl type fingerprint - the most plausible valid pattern. Figure 3 shows comparisons with other methods available in literature.

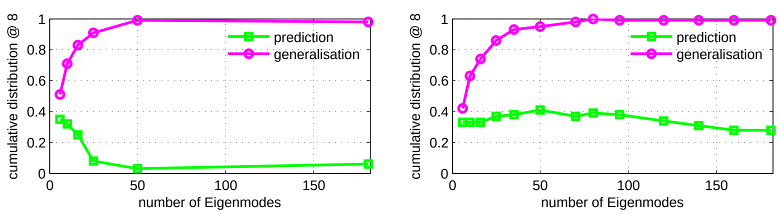
4.3 Estimating the Number of Modes

In order to estimate the best number of Eigenmodes we performed the above mentioned prediction and generalisation experiments for a varying number of Eigenmodes. The evaluation criteria for the prediction and generalisation figures was the relative number of fingerprints with less than eight degrees average error. Due to the computational burden, only the first 100 images of the NIST4 database (s-prints) were used. We performed this evaluation for two scenarios. In the first scenario (shown in Subfigure 4(a)) one can see how the number of coefficients affects the model without regularisation. Furthermore, it shows the trade off between generalisation and prediction capability of the method. In general, a lower number of Eigenmodes results in good prediction figures but bad generalisation capability of the model - and vice versa. The second scenario (see Subfigure 4(b)) shows the model as proposed with the regularisation. It is clearly visible that the regularisation leads to a significant improvement.



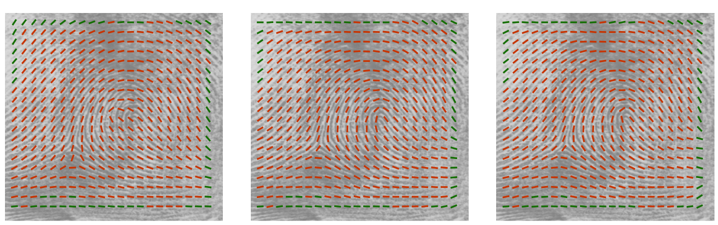
(a) *input OF highlighted* (b) *proposed* (c) *FOMFE, 162 parameters* (d) *Legendre Polynomials*

Fig. 3. Prediction ability of various methods proposed in literature. Input OF as shown in 3(a). Green color is used to display the interpolated/extrapolated OF. Subfigure 3(b) shows the results of the proposed method. The prediction cabability of the FOMFE approach (exactly as in [14]) is shown in image 3(c). Subfigure 3(d) shows results of the approach described in [11] (exactly as described in the paper). Note that the proposed method (Figure 3(b)) generates the most plausible OF.



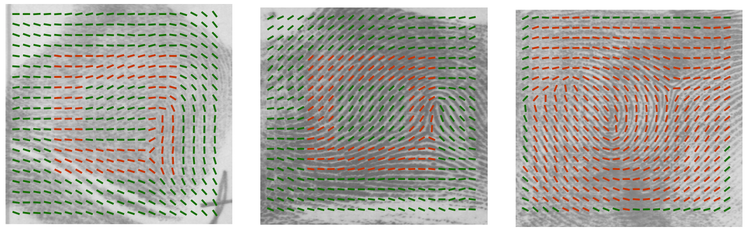
(a) *no regularization* (b) *with regularization*

Fig. 4. Regularisation. Applying a regularisation on the cost function, where we force the orientation vectors to unit length, we can significantly improve the results.



(a) *5 Eigenmodes* (b) *80 Eigenmodes* (c) *182 Eigenmodes*

Fig. 5. Number of Eigenmodes. In case of to few Eigenmodes (Subfigure 5(a)) the model fails to generalize, especially visible at SPs. The application of a higher number of Eigenmodes allows the model to fit the shown OF more precisely.



(a) *rotation* (b) *translation* (c) *upside down of 5*

Fig. 6. Subfigure 6(a) shows a 45 degree rotated fingerprint image. In Subfigure 6(b) an uncentered loop type fingerprint is shown. Figure 6(c) displays an upside down loop which has been corrected to a whorl. Predicted OF is shown in green.

4.4 Conclusion

In this paper we presented a statistical model for fingerprint ridge orientation. The fingerprint orientation field (OF) can be constrained by the Active Fingerprint Ridge Orientation Model (AFROM) to vary only in ways seen in a training set. The OF of fingerprints is represented by a vectorially linear regression using Legendre Polynomials. Fitting parameters to a given fingerprint is done using the Levenberg-Marquard (LM) algorithm. During the optimization procedure the parameters are limited to a previously learned linear subspace, where only 'legal' fingerprints reside. Using the proposed method, the AFROM iteratively deforms to fit an OF of a fingerprint. Our method does not depend on any prealignment or registration of the considered images. The training can be done fully automatic without any user interaction. Furthermore, our method does not depend on any other computed data, except a segmentation.

In the evaluation section of this paper, we perform generalisation and prediction tests of the proposed method. A generalisation test is done in order to evaluate how well the model 'fits' to a large number of OFs. Using the presented prediction test, we asses how specific the model is. This is the ability to constrain unknown or noisy regions of the OF to valid fingerprint flow patterns. All experiments are performed on public databases (from which one is fairly different to the learning dataset). These experiments, comparable with a very recent paper [6], assess our method a very good performance. Furthermore, it should be noted that our method is the first fingerprint OF model making use of prior knowledge for OF estimation. The major conception behind existing methods (e.g. [6]) is a hand crafted model which fits only to valid fingerprint OFs, without the possibility for machine based training. Our approach can also be seen as a method to find those elements (Eigenmodes comply to 'Eigen-Orientations') which, when (linear) combined, give biological valid patterns of fingerprints. We want to point out, that we used the full NIST4 f-prints database for training, including many noisy fingerprint images.

Future work includes the experimentation with other subspace methods than PCA (e.g. ICA, K-PCA, etc.). Moreover, the regularization term of the cost functional accommodates a large potential for future improvements. Another topic is the inclusion of an image quality estimation algorithm, where the model adjusts the amount of prior knowledge depending on the local image quality.

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