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Fingerprint Registration Using Composite Features Consensus

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Abstract. The paper presents a fingerprint registration approach based on the decomposition of registration process into elementary stages. In each stage a single transformation parameter is eliminated. The algorithm uses composite features, i.e., lines connecting two minutiae instead of fingerprint minutiae. These features have rotation and translation-invariant attributes allowing feature filtering with significantly enhanced signal-to-noise ratio in feature consensus scheme. Experimental results of goal-directed performance evaluation with live-captured fingerprint image database are presented.

Key words: fingerprint, registration, features consensus.

1. Introduction

Automatic fingerprint recognition technologies currently have wide application for biometric person identification (Finger Technologies Survey, 1999; Jain *et al.*, 1997). The purpose of identification system is to check matching between the person's fingerprint with all fingerprint records, earlier enrolled and stored in the database. Person's verification solves similar task where system uses previously declared persons identificator and checks matching between two fingerprints only. Use of such systems depends on discrepant requirements, first of all, identification reliability, matching speed and system cost. Though many identification algorithms (Isenor and Zaky, 1986; Jain *et al.*, 1986) as well as commercial systems (Finger Technologies Survey, 1999) are proposed, achieving satisfactory fulfillment of all discrepant requirements is still important problem.

Most of the automatic fingerprint recognition systems follows manual fingerprint verification scheme and uses a set of specific fingerprint points (minutiae) as fingerprint features. Fingerprint minutiae is usually defined as an end or branching point of the ridge of the capillary line, and are described by point coordinates and ridge directions (Hong *et al.*, 1998). Types and locations of the minutiae are unique for every individual. The process of automatic minutiae extraction depends heavily on the quality of an input fingerprint image, and in case of poor quality set of extracted minutiae may have false or missing minutiae. Fingerprint matching systems usually receive only partially overlapping minutiae sets for comparison. During the last two decades some standard steps in fingerprint minutiae extraction process were defined: smoothing of grayscale fingerprint image, evaluation of ridge orientation field, localization of fingerprint regions with acceptable quality, ridge extraction and image binarization, ridge thinning, minutiae detection and false minutiae elimination. These steps are at least partially implemented in fingerprint identification systems described in the literature (Isenor and Zaky, 1986; Jain *et al.*, 1986).

The template (query) fingerprints may be rotated, translated or scaled with respect to the reference fingerprints. The recognition algorithm should therefore be rotation, translation and scaling-tolerant. In biometric applications template and reference fingerprints are usually scanned by the same scanner. If not, resolutions of the different scanners are known, so the scaling tolerance is usually not necessary for the recognition algorithm. Finally, depending on the applied pressure and position of the finger during the fingerprint acquisition, the fingerprint may undergo various nonlinear deformations, which leads to additional perturbations in the identification process.

One of the commonly used approaches to deal with relative fingerprint rotation and translation is to eliminate them using a preliminary fingerprint registration algorithm (Jain *et al.*, 1986). In this stage relative rotation and translation between the two fingerprints feature sets are established, and then the feature sets are oriented and placed in the right positions.

Various image registration algorithms were proposed in literature. One of these approaches is based on Hough transform (Ratha *et al.*, 1996; Stockman *et al.*, 1982), where for each point in discretized transformation parameter space, matching score is computed using all pairs of features from two fingerprints. The point in parameter space with maximum matching score is selected as the transformation between the fingerprints. Such algorithm is quite slow, because for all allowed points in the transformation parameter space, feature matching must be calculated. To eliminate this problem, many hierarchical schemes, which use reduction of initial image resolution or other methods for reduction of initial information content and decrease required number of comparisons (Lester and Arridge, 1999), were proposed.

Some registration approaches are specific to fingerprint matching. In (Chong *et al.*, 1997) the registration algorithm is based on delta and center fingerprint singular points. However, such method does not work if fingerprint does not have these points or these points are not visible in the processed part of fingerprint. Another method is based on the association of fingerprint minutiae with corresponding ridges (Jain *et al.*, 1986). This method requires ridge extraction from fingerprint image, and can be not reliable in case of noisy image, or if only a short ridge is associated to the feature, etc.

In (Shekhar *et al.*, 1999) the algorithm for multisensor image registration using feature consensus was proposed. According to it, image registration is decomposed into elementary stages, and at each stage single geometric transformation (scaling, rotation, translation etc.) parameter is estimated. Necessary condition for this algorithm is the possibility to decompose the original transformation T into the sequence of simpler geometric transformations characterized by a single parameter. Choice of image features and their geometric attributes for estimate of transformation parameters is guided by the introduced concept of observability. Let I and I' denote the images to be registered and T_θ is the current stage of transformation. Consider the pair of features f and f' of the same type (points, lines, edges, etc), where f is from the image I and f' is from image I'. If features f and f' have the attributes α and α' related by a bijective function $\alpha' = g_\theta(\alpha)$, the parameter θ is called observable with respect to the feature class $\boldsymbol{f}$ and the attribute class $\boldsymbol{\alpha}$, where class $\boldsymbol{f}$ is the set of all features of the same type as f and f' and $\boldsymbol{\alpha}$ is the set of α type attributes associated with the feature class $\boldsymbol{f}$. It is assumed that function g_θ permits the parameter to be estimated as $\theta = h(\alpha, \alpha')$. The feature pair (f, f') casts a single vote for the estimated value of the transformation parameter. The votes are accumulated in a function called consensus function $H(\theta)$. The feature consensus mechanism determines the transformation parameter which is simply the value of θ which maximizes the consensus function. Finally, the estimated transformation is applied to one of the images, and the algorithm proceeds to next stage.

Most interesting transformation in the fingerprints registration the is the similarity transformation (Shekhar *et al.*, 1999)

$$\boldsymbol{p}' = sR_\beta \boldsymbol{p} + \boldsymbol{t},$$

which is characterized by four parameters: rotation angle β, translation t_x and t_y and scale s. The transformation can be registered by three steps.

1. Rotation angle determination. The rotation angle β, is observable from the slopes of line features in the images. If l and l' are corresponding line features from the images I and I' with slope angles φ and φ' respectively, the relation between angles can be expressed as

$$\varphi' = \varphi + \beta.$$

Thus β can be determined by consensus of line features and the estimated rotation can be applied to the first image.

2. Scale determination. The observing attribute is a distance d between the two points. The relation between the distances is:

$$d' = sd.$$

3. Translation determination. The observing attribute is a location p_x, p_y of point feature. Relations between the coordinates are:

$$p'_x = p_x + t_x$$

and

$$p'_y = p_y + t_y.$$

To improve the algorithm performance, authors (Shekhar *et al.*, 1999) propose to use progressive feature filtering method. According to this method, the observing feature pair vote only if it is similar according to some other attributes, which are invariant with respect to the transformation set left to estimate.

In this paper we adopt the feature consensus algorithm for the registration of rotated and translated biometric fingerprints. The specific feature of this application is usage of the registration algorithm not only to fingerprints of the same finger but also to fingerprints of different fingers. Eventually, this affects whole process of fingerprint identification. For the sake of simplicity and efficiency, our algorithm is based only on the standard set of extracted minutiae and their three attributes, namely coordinates in 2D space and directions. It will be shown that for successful application of the feature consensus algorithm feature filtering is required in order to increase signal-to-noise ratio. The remaining part of this paper is organized as follows. In Section 2, a composite fingerprint features which enable the use of the progressive feature filtering, are introduced. In Section 3, we propose the fingerprint registration algorithm using these features. The experimental results obtained using fingerprints, captured with optical fingerprint scanner, are presented in Section 4. Finally, the experimental comparison between the proposed registration method and Hough transform-based registration method is described in Section 5.

2. Lines Between Minutiae as Composite Fingerprint Features

The consensus-based registration algorithm can be directly implemented using the minutiae coordinates and directions. The rotation parameter is observable from the minutiae direction and the translation parameter is observable from the minutiae coordinates. For the rotation angle estimation step, there are no available attributes invariant to the rotation and translation transformations, thus each pair of minutiae from the two fingerprint images should vote for the rotation parameter. Great majority of these pairs vote for an incorrect rotation angle, and thus contribute to the noise component of the consensus function, and heavily degrade signal-to-noise ratio (Shekhar *et al.*, 1999). In addition, large fingerprint areas may have minutiae clusters with similar directions and coordinates, thus spurious peaks are formed in consensus function. In the second translation elimination step, the minutiae angle is invariant to the translation and can be used to filter voting pairs of minutiae. As it will be shown in Section 4, without this filtering performance of consensus registration algorithm is totally unacceptable.

We propose the new composite features, namely lines connecting the two minutiae points, enable us to use voting pair filtering in both steps, yielding significant improvement of the registration algorithm at the cost of increased complexity of the algorithm.

Let us assume that we have a template fingerprint minutiae collection

$$Q = \big((x_1^K, y_1^K, \varphi_1^K), \ldots, (x_N^K, y_N^K, \varphi_N^K)\big),$$

and a reference fingerprint minutae collection

$$P = \big((x_1^L, y_1^L, \varphi_1^L), \ldots, (x_M^L, y_M^L, \varphi_M^L)\big),$$

where x, y are the coordinates of a minutiae point and φ is the minutiae direction. The line feature K_{ij} associated i and j minutiae $(i \neq j)$ of the template fingerprint is described by the following set of attributes:

$$K_{ij} = \left[\left((x_i^K, y_i^K, \varphi_i^K, x_j^K, y_j^K, \varphi_j^K, d_{ij}^k, \Phi_{ij}^K, \bar{\omega}_i^K, \bar{\omega}_j^K)\right)\right].$$

Where d_{ij} is a Euclidean distance between i and j minutiae,

$$\Phi_{ij}^K = \mathrm{artcg}\left(\frac{x_i^K - x_j^K}{y_i^K - y_j^k}\right),$$

is the line direction, and

$$\bar{\omega}_j^K = \Phi_{ij}^K - \varphi_j^K,$$
$$\bar{\omega}_i^K = \Phi_{ij}^K - \varphi_i^K$$

are the angles between the line directions and the minutia directions at both ends of the line.

The total number of lines, which can be created for all possible minutiae pairs is $N(N-1)$. However, in order to reduce computational complexity and to increase robustness of the algorithm, we use only those pairs of minutiae which have distance attribute within certain interval:

$$d_{\min} < d_{ij}^K < d_{\max}.$$

In addition, maximum number of fingerprint lines is limited by the value $K_{\max}$.

Similarly, the line between the k and l minutiae in the reference fingerprint is described by the set:

$$L_{kl} = \left((x_k^L, y_k^L, \varphi_k^L, x_l^L, y_l^L, \varphi_l^L, d_{kl}^L, \Phi_{kl}^L, \bar{\omega}_k^L, \bar{\omega}_l^L)\right).$$

It should be noted, that symmetric line pairs (i.e., for the (i, j) minutiae pair two lines: from i to j and from j to i) should be created for the template. For the reference fingerprint image the lines are created if $l < k$. This is related to the fact that the line associated with the (m, n) minutiae pair is not equivalent to the line associated with the (n, m) minutiae pair, and the numbering of the minutiae in each fingerprint is independent and undefined. If the restriction $m < n$ would be respected during the line creation in both template and reference fingerprints, lines in the same pair of minutiae may be created in opposite directions and as a result, matching line pairs may be lost.

3. Fingerprint Registration

The fingerprint registration algorithm proposed in this section in general follows the main guidelines of the algorithm presented in (Sheklar *et al.*, 1999). The attention will be paid to the feature filtering process which enables to reduce the number of voting pairs and greatly increase the signal-to-noise ratio in consensus function. For this purpose, appropriate line attributes, which are invariant to the image rotation or translation or invariant to the both transformations, are used.

3.1. *Elimination of Relative Fingerprint Rotation*

The rotation angle Θ is observable only for the line direction attribute Φ. The other three attributes

$$d_{ij}^K,\ \bar{\omega}_i^K,\ \bar{\omega}_j^K$$

of the line K_{ij} are invariant to the image rotation, and translation thus will be used to reduce the number of voting pairs in this step. Each pair of lines (K_{ij}, L_{kl}), where the lines K_{ij} and L_{kl} belong to the template and reference fingerprint datasets respectively, should pass the comparison process to cast the vote for their relative rotation angle $\Delta\Phi$:

$$\Delta\Phi_{K_{ij}L_{kl}} = (\Phi_{ij}^K - \Phi_{kl}^L) \bmod 360.$$

Let us define

$$\Delta\bar{\omega}_1 = \begin{cases} a, & \text{if } \left(a = \left(\bar{\omega}_i^K - \bar{\omega}_k^L\right) \text{mod} 360 < 180,\right. \\ 360 - a, & \text{otherwise,} \end{cases}$$

$$\Delta\bar{\omega}_2 = \begin{cases} a, & \text{if } \left(a = \left(\bar{\omega}_j^K - \bar{\omega}_l^L\right) \text{mod} 360 < 180,\right. \\ 360 - a, & \text{otherwise,} \end{cases}$$

$$\Delta d = \left|d_{ij}^K - d_{kl}^L\right|.$$

The rotation and translation-invariant similarity value $C(K_{ij}, L_{kl})$ is defined as follows:

$$C\left(K_{ij}, L_{kl}\right) = \left\{ \begin{array}{l} a, \text{ if } \left(a = c_{\text{thresh}}^R - a_1\Delta d - a_2\Delta\bar{\omega}_1 - a_3\Delta\bar{\omega}_2\right) > 0, \\ 0, \text{ otherwise,} \end{array} \right\}$$

where coefficients a_1, a_2 and a_3 control the tolerance for the difference between corresponding attributes, and are defined experimentally. If the value $C(K_{ij}, L_{kl})$ is positive, then the lines from (K_{ij}, L_{kl}) pair matche each other.

Finally, the rotation consensus function $H^R(\Theta)$ is defined as:

$$H^R(\Theta) = \sum_{\substack{\text{all matching pairs} \\ (K_{ij}, L_{kl})}} \delta\left(\Theta - \Delta\Phi_{K_{ij}L_{kl}}\right),$$

i.e., each pair of lines (K_{ij}, L_{kl}), which passes matching test, adds 1 to the consensus function $H^R(\Theta)$ at a $\Delta\Phi_{K_{ij}L_{kl}}$ bin. The resulting value of relative fingerprint rotation angle is estimated as the value of Θ that maximizes the consensus function:

$$\Theta = \arg\max_{0<\lambda<360} \left(H^R(\lambda)\right).$$

And finally, the collection of lines from the template fingerprint is transformed according to the estimated rotation angle:

$$K_{ij}^R = \left((x_i^R, y_i^R, \varphi_i^R, x_j^R, y_j^R, \varphi_j^R, d_{ij}^K, \Phi_{ij}^R, \bar{\omega}_i^K, \bar{\omega}_j^K)\right),$$

where

$$\begin{aligned}
\Phi_{ij}^R &= \Phi_{ij}^K + \Theta,\\
\varphi_j^R &= \varphi_j^K + \Theta,\\
\varphi_i^R &= \varphi_i^K + \Theta,\\
y_i^R &= y_i^K \sin\Theta - y_i^K \cos\Theta,\\
x_i^R &= x_i^K \cos\Theta + y_i^K \sin\Theta,\\
y_j^R &= y_j^K \sin\Theta - y_j^K \cos\Theta,\\
x_j^R &= x_j^K \cos\Theta + y_j^K \sin\Theta.
\end{aligned}$$

It is helpful to mention here, that weighting of votes by the similarity value $C(K_{ij}, L_{kl})$ does not change the performance of registration algorithm on the tested set of the fingerprints.

3.2. *Elimination of Relative Fingerprint Translation*

The translation elimination step is similar to the rotation elimination step. However, after the elimination of the rotation it is possible to use the new attributes φ_i^R and φ_j^R along with the line Φ_{ij}^R direction in the feature filtering, since these parameters are invariant to translation. On the another hand, the parameters ω_i^K, and ω_j^Kdepend on Φ_{ij}^R, φ_i^R, and Φ_{ij}^R, φ_j^R, respectively, and cannot be useful in this stage. Therefore, for independent d_{ij}^K, Φ_{ij}^R, φ_i^R and φ_j^R parameters invariant to translation, we can define Δd, $\Delta\Phi$, $\Delta\varphi$ and $\Delta\varphi$, just like we did in rotation elimination stage.

The translation-tolerant similarity value $T(K_{ij}, L_{xy})$ is:

$$T\left(K_{ij}, L_{kl}\right) = \left\{ \begin{array}{l} a, \text{ if } (a = c_{\text{thresh}}^T - a_4\Delta d - a_5\Delta\varphi_1 - a_6\Delta\varphi_2 - a_7\Delta\Phi) > 0, \\ 0, \text{ otherwise.} \end{array} \right\}.$$

Lines K_{ij} and L_{kl} are considered as matching pair, if $T(K_{ij}, L_{kl})$ is positive.

For each pair of lines (K_{ij}, L_{kl}) the translation parameters Δx and Δy are calculated as follows:

$$\Delta y_{K_{ij}L_{kl}} = \frac{(y_i^R - y_k^L) + (y_j^R - y_i^L)}{2},$$

$$\Delta x_{K_{ij}L_{kl}} = \frac{(x_i^R - x_k^L) + (x_j^R - x_i^L)}{2}.$$

The consensus functions $H^x(\Theta)$ and $H^y(\Theta)$ are defined as:

$$H^x(\Theta) = \sum_{\substack{\text{all matching pairs}\\(K_{ij},L_{kl})}} \delta\left(\Theta - \Delta x_{K_{ij}L_{kl}}\right),$$

$$H^y(\Theta) = \sum_{\substack{\text{all matching pairs}\\(K_{ij},L_{kl})}} \delta\left(\Theta - \Delta y_{K_{ij}L_{kl}}\right),$$

The translation values are estimated by finding the global peaks of smoothed translation consensus functions. Coordinates in the feature sets Q and P are aligned according to these values.

4. Experimental Results

Fingerprint registration is an intermediate step which aids to facilitate fingerprint matching process. Thus, evaluation of accuracy of the fingerprint identification system employing the presented registration algorithm as a component, gives reliable goal-directed performance evaluation (Hong *et al.*, 1998). Since true fingerprint identification is possible only after correct registration, recognition false rejection rate is also maximum possible wrong registration rate.

We have tested our fingerprint identification system on a set of fingerprints captured with optical fingerprint scanner at 340 dpi resolution. The set contains 75 fingerprint images belonging to 15 different persons (i.e., 5 fingerprints of each finger). Possible variations of finger position and orientation are demonstrated in Fig. 1. As can be seen from the figure, differences are most prominent in finger positioning (Figs. 1a, 1b), while variations in orientation are less expressed (Figs. 1c, 1d). Quality of fingerprint images in our database ranges from good (Fig. 2a) to poor (Fig. 2c).

The description of algorithm employed by our fingerprint identification system used in the experiments is not yet published. It consists of minutiae extraction, fingerprint registration (presented in this paper), and matching score calculation steps. Brief description of first and last steps will be presented below. The minutiae extraction step follows general guidelines mentioned in the introduction, and consists of pre-smoothing and contrast standardization, direction field estimation, smoothing using directional windows, binarization, skeletonization, and finally, robust minutiae extraction stages. The matching score was calculated by a simple algorithm which places bounding boxes around each

Fig. 4.1. Illustration of database fingerprints obtained at various finger positions and rotation angles.

minutiae in the query fingerprint, thus allowing to tolerate to some extend the minutiae position and orientation differences in the aligned reference fingerprint. In experiments with line features, matching score was calculated as a sum of lines matching values, i.e., matching values of corresponding minutiae pairs in query and reference fingerprints. In experiments with minutiae features matching score was calculated as a sum of single minutiae matching values.

All fingerprints from the dataset were registered with four different fingerprints of the same finger (300 comparisons) and with all other fingerprints in the database (5250 comparisons). In the registration algorithm, the following parameter values were used:

$$d_{\min} = 40,\ d_{\max} = 130,\ K_{\max} = 300,\ c^{R}_{\text{thresh}} = 23,\ c^{T}_{\text{thresh}} = 28,$$
$$a_1,\ a_2,\ a_3,\ a_4,\ a_5,\ a_6,\ a_7 = 1.$$

The identification was accomplished by selecting the threshold, and classifying fingerprints with the matching score greater than the threshold as belonging to the same finger. The identification results are presented by *receiver operating curves* (ROC), which express dependence of authentic acceptance rate from false acceptance rate. Fig. 3 illustrates the importance of feature filtering in feature consensus algorithm. The figure shows experimentally obtained ROC's using line features with and without feature filtering. As it

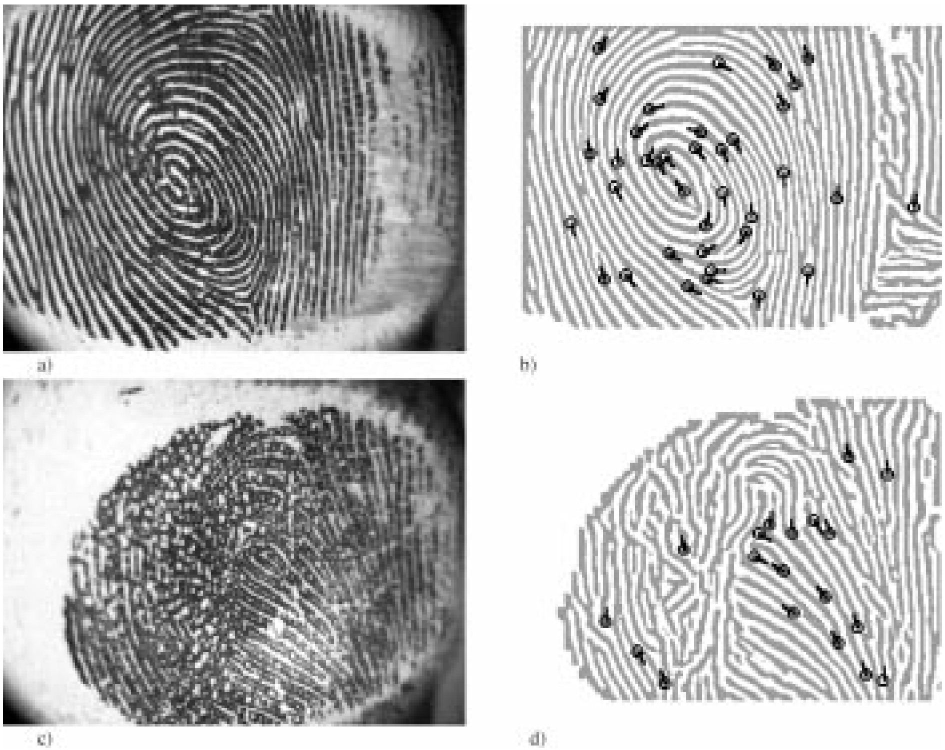

Fig. 4.2. Illustration of fingerprint quality in the database (a – original images of good quality, c – original images of bad quality, b,d – their respective binarized images with minutiaes extracted).

is seen from the figure, the true acceptance rate is much higher with feature filtering at the same level of false acceptance. This is especially evident when comparing true acceptance rate at threshold values, close to which false acceptance rate reaches 0.01%: 87% and 42% for registering with and without feature filtering, correspondingly. It can also be mentioned that when using registering without filtering, 100% authentic acceptance rate is never reached, since in about 25% of cases matching two fingerprints of the same finger give matching score equal zero. It is therefore impossible to select an appropriate threshold.

Fig. 3 also shows difference between ROC obtained in experiments using line features and with ROC obtained in experiments using minutiae features. The ROC obtained using minutiae is significantly lower. At 0.01% level false acceptance rate it reaches only 79% of true acceptance rate. At 1% false acceptance level true acceptance rates are 94% and 81% for line and minutiae features, respectively.

For an on-line verification system identification time is of major importance. Our system, depending on the number of selected features in query fingerprint, is capable of checking 50–80 matches per second on a PC computer with Pentium II 400 MHz processor. The registration algorithm takes most of the time, since feature pairs rejected in registration step as non-matching are not considered in matching score calculation step.

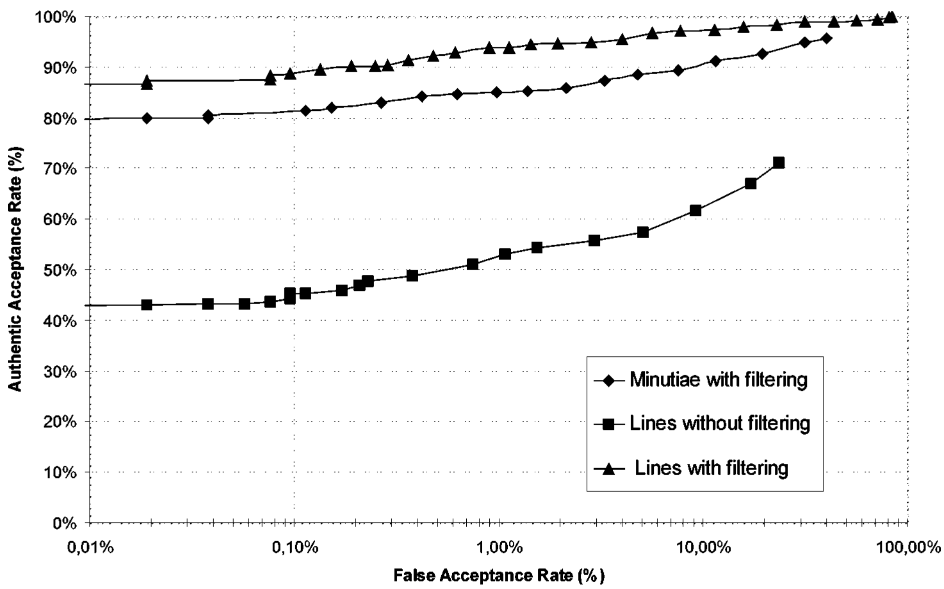

Fig. 4.3. Receiver Operating Curves, showing improvement of verification performance using lines and progresive features filtering.

5. Comparison with Hough Transform-Based Registration Algorithm

The Hough transform-based feature detection and matching algorithms are predecessors of the feature concensus algorithm. Although the superiority of feature consensus algorithm from the point of view of computational complexity and computer resources usage is quite obvious it is interesting to compare them from the standpoint of the registration quality.

We implemented Hough transform algorithm proposed in (Isenor and Zaky, 1986) for the registration of fingerprint images. This algorithm works directly on minutia sets extracted from two fingerprint images. The selected Hough space discretization intervals are 5 pixels along translation axes and 7 degrees along the rotation axis. This selection was made as an optimal after sparse tryouts in the region which was chosen taking into account possible errors in the position and direction of extracted minutia.

In the goal-directed performance evaluation we used the same database, fingerprint processing, minutia extraction and matching algorithms as in the experiments, described in the previous section. The comparison of the ROCs presented in Fig. 4. reveals that feature consensus-based registrations can give significantly better result than Hough transform-based registration. At the 0.01% level of false acceptance rate, true acceptance rate for Hough transform-based registration reaches only 82%, while for the feature consensus-based registration it reaches 87%. At the 1% level of false acceptance rate, true acceptance rates are 94% and 84%, respectively.

It should be also noticed, that Hough transform-based registration is 25 time slower and requires more computer memory than the proposed method.

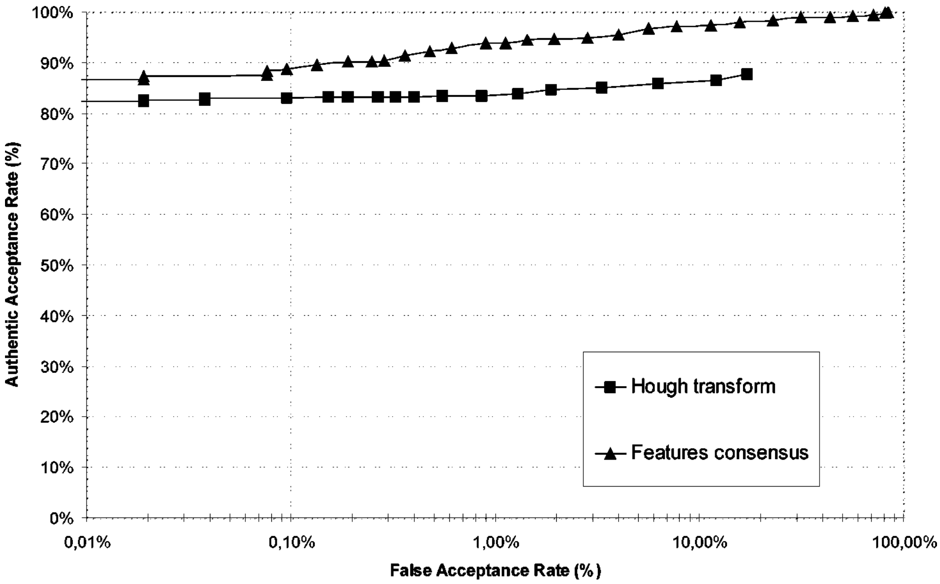

Fig. 5.1. Comparisson of Hough transform and features consensus based fingerprints registration.

6. Conclusions

We have described a fingerprint registration algorithm based on feature consensus method, according to which geometric transformation relating two fingerprints is decomposed into a sequence of simpler transformations described by a single parameter, and each transformation is estimated by calculating the votes castled by pairs of the features from the two fingerprints for the transformation consistent with the pair. The algorithm employs only fingerprint minutiae coordinates and directions, i.e., features that are used virtually in any fingerprint identification system. This enables straightforward incorporation of the registration algorithm into working identification systems, even in cases when minutiae are in advance extracted and stored in a separate database.

In the original paper (Sheklar *et al.*, 1999) the feature consensus algorithm was argued to be a feature correspondenceless algorithm, provided that the peak in consensus function formed by correct transformation is not hidden by accident peaks. We demonstrate experimentally that in fingerprint images this assumption is not valid, and in order to achieve acceptable performance, feature matching and filtering is required. To enable feature filtering in both rotation and translation stages, we introduce a composite feature, line which connects two minutiae. The goal-directed performance evaluation was conducted by assessing accuracy of the fingerprint identification incorporating the registration algorithm as a component. The experiments with 75 fingerprint images database give 94% true acceptance rate at 1% false acceptance rate.

Tests on a PC computer with Pentium II 400 MHz processor show that the investigated registration algorithm ensures recognition speed suitable for using in most biometrical applications with medium-sized databases.

The comparison with Hough transform-based registration method shows that proposed algoritm allows to achieve better registration quality and speed.

References

Chong, M., T.H. Ngel, L. Jun, R. Gay (1997). Geometric framework for fingerprint clasification, *Pattern Recognition*, **30**(9), 1475–1488.

Finger technologies survey (1999). *Biometric Technology Today*, **6**(10), 8–16.

Hong L., *et al.* (1998). Fingerprint image enchancement: algorithm and performance evaluation. *IEEE Trans. Pattern Analysis and Machine Inteligence*, **20**(8), 777–789.

Isenor D.K., S.G. Zaky (1986). Fingerprint identification using graph matching, *Pattern Recognition*, **19**(2), 113–122.

Jain A., L. Hong, R. Bolle (1997). On-line fingerprint verification. *IEEE Trans. Pattern Analysys and Machine Inteligence*, **19**(4), 302–314.

Lester H., S. Arridge (1999). A survey of hierarchical non-linear medical image registration. *Pattern Recognition*, **32**, 129–149.

Ratha N., K. Karu, S. Chen, A. Jain (1996). A real time matching system for large fingerprint databas. *IEEE Trans. Pattern Analysis and Machine Inteligence*, **13**(8), 799–813.

Shekhar Ch., V. Govindu, R. Chellappa (1999). Multisensor image registration by feature consensus. *Pattern Recognition*, **32**, 39–52.

Stockman G., S. Kopstein, S. Benett (1982). Matching images it models for registration and object detection via clustering. *IEEE Transactions on Pattern Analysis and Machine Inteligence*, **4**(3), 229–241.

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Pirštų antspaudų registravimas pagal sudėtinių požymių konsensusą

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Darbe pateiktas pirštų antspaudų reliatyvaus posūkio ir postūmio eliminavimo (registravimo) būdas, naudojant sudėtinius požymius, t. y. linijas jungiančias du piršto antspaudo požymius. Šių požymių posūkiui ir poslinkiui invariantiški atributai leidžia naudoti efektyvų požymių filtravimą ir padidinti signalo/triukšmo santykį požymių konsensuso schemoje. Darbe pateikti eksperimentiniai duomenys su pirštų antspaudais, naudojamose biometrinėse asmens identifikavimo sistemose.