RECONSTRUCTION-FREE MATCHING FOR FINGERPRINT SWEEP SENSORS

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ABSTRACT

Many different types of silicon fingerprint sweep sensors presently enter the biometrics market. Since they provide small stripe image sequences instead of full fingerprint images, they require new matching algorithms.

This paper presents a new one-stage, Viterbi-based matching approach which can be directly applied to the raw sweep sensor output. This is in contrary to the conventional two-stage approach where the stripe image sequences are combined to area images in a reconstruction step and subsequently fed into a recognition system appropriate for area images. Simulation results prove that the new algorithm is superior to the conventional two-stage system in terms of recognition performance and maximum allowed finger sweeping speed.

1. INTRODUCTION

From all the biometric modalities fingerprints are considered to have the highest market potential combining a high user acceptance with a good biometric performance. While fingerprint *area* sensors are already in the field for a long time, presently many different types of so called *sweep sensors* based on silicon technology are appearing on the market. Because these sensors are covering a small silicon area only, they are cheap enough to capture the new mass market of embedded devices [3].

Sweep sensors have a sensing area spreading over the width of a finger but covering only a small distance perpendicular to it. To obtain the full fingerprint information, the sensor has to capture images continuously while the finger is moving along the sensor area.

Along with the first sensor of this type, a straightforward, *two-stage* processing principle was established [2], [3]:

1. Reconstruct a geometrically correct area image out of consecutive image stripes using the finger sweeping speed information. The speed information can implicitly be estimated out of the stripe overlap.

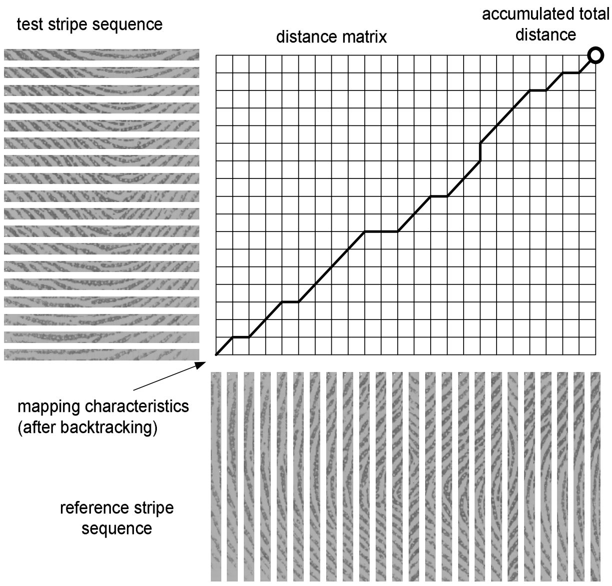

Figure 1: schematic diagram for direct stripe matching.

2. Feed the reconstructed image into a conventional matching system suitable for area sensors.

If the sweep sensor is sequentially scanning the image lines, an image stripe is distorted due to the finger movement. To obtain a geometrically correct area image after reconstruction, this distortion has to be corrected.

The new approach described in this paper establishes a *one-stage* or *direct* recognition system for sweep sensors. This system is able to do a direct match between image stripe sequences by defining a (local) distance measure between image stripes, applying a Viterbi search to find the optimal mapping between two complete stripe sequences, and provide a global match score at the same time ([6], s. fig. 1).

The new approach does not require an explicit image reconstruction any more which results – together with the used Viterbi search – in several advantages compared to the conventional two-stage approach:

1. There is no need for an overlap between image stripes for reconstruction anymore. This allows higher finger speeds with the identical sensor hardware.
2. The robustness is higher since the mapping of the finger stripes is done in a global optimal way so that a few corrupted image stripes in a sequence will hardly influence the recognition results. In contrast, single corrupted frames can totally destroy the geometry of a reconstructed image making recognition impossible.
3. Generally, it can be assumed that the global optimal mapping leads to a better system performance than the local pair by pair image stripe reconstruction.

The paper is structured as follows: after a system overview explaining the new approach and certain variations in more detail (s. sec. 2) the used databases and evaluation metrics are described in sec. 3. Simulation results for system characterization and comparison are presented in sec. 4 leading to the conclusions in sec. 5.

2. SYSTEM OVERVIEW AND ALGORITHMS

2.1 Basic system and algorithms

In its basic form the direct comparison of two image stripe sequences can be used for verification as follows:

(1) Local match: compare all M image stripes of a test sequence to all N stripes of a reference sequence using a normalized 2-dimensional template correlation [4]. Store the individual distances $d_{mn} = 1 - c_{mn}$ derived from the correlation coefficients c_{mn} in a MxN distance matrix **D**.

(2) Viterbi search: iteratively accumulate the local distances using the Viterbi algorithm with different weights for diagonal and straight transitions resulting in the accumulated distance matrix **A**:

$$a_{m,n} = \min(a_{m-1,n-1} + \sqrt{2} \cdot d_{m,n}, a_{m,n-1} + d_{m,n}, a_{m-1,n} + d_{m,n})$$

In parallel, feed the transition matrix **B** (if needed for backtracking) and path length matrix **L** (for subsequent path length normalization) [6].

(3) Global match: search minimum accumulated distance normalized by path length in first row $a_{M,n}/l_{M,n}$ and last column $a_{m,N}/l_{m,N}$ respectively. This defines the total match score $S_r = 1 - \min(a/l)$ of a test sequence matched against the reference sequence r.

In case of identification steps (1) – (3) are repeated for all R reference sequences. The index of the sequence with the maximum match Score $r_{\max}$ provides the result.

2.2 Accelerating by reducing redundancy

The 2D correlation is the straightforward way to compare image stripes. This method is used to show the principal functionality of the direct stripe match system and as a basis for algorithm comparisons.

It can be anticipated that the 2D correlation is computational very expensive. For that reason additional methods were introduced to reduce the amount of data before the image stripes are compared:

- **Vertical average:** Since an image stripe **F** is only a few pixels in height (in evaluation constantly 8 pixels, s. sec. 3), the image content of consecutive image lines normally does not change very much. For that reason it can be assumed that the whole stripe $\mathbf{F}(x,y)$ can be represented by a 1D function $\bar{f}(x) = \frac{1}{8}\sum_{y=1}^{8} \mathbf{F}(x,y)$ averaging the columns vertically. These functions can be compared by a 1D correlation which speeds up matching considerably.
- **Fourier features**: The correlation step using the vertical average function is necessary to compensate for horizontal finger displacements. To avoid this step new features are built as the magnitude of the discrete Fourier transform $|\,\mathrm{DFT}\{\bar{f}(x)\}\,|$ which is invariant to translation. The components of the Fourier feature vector are normalized to equalize the value range. The distance between vectors is defined by the Euclidian distance measure.

It is not claimed that the presented features are the optimal ones. But they should be appropriate to show whether a feature-based stripe sequence matching is feasible.

3. DATABASES AND EVALUATION METRICS

3.1 Synthetically generated and decomposed images

To study the basic behavior of the new approach synthetically generated *area* images were generated using the *Sfinge* tool ([1], example s. fig. 2). Afterwards, these area images are decomposed into stripe sequences using a proprietary tool (stripe size 256x8 pixels). This way many sensor (e.g. contrast, ridge width, dirt attractiveness, internal sensor timings) and usability parameters (e.g. finger sweeping speed, shearing, and rotation) can be exactly controlled and their effect on the algorithms can be studied. The generated database contains 10 users with one reference and 4 test fingerprints each.

3.2 Real sweep sensor images

The real image sequences were obtained with a prototype silicon sweep sensor (sensor area 256x8 pixels). The database contains fingerprints from 3 users taken from 4 different fingers each (12 virtual users). Each fingerprint was taken 5 times. There were no restrictions concerning finger sweeping speed and rotation. (example s. fig. 2).

Figure 2: example of synthetic fingerprint (left, before decomposition) and sweep sensor image of real finger (right, reconstructed).

3.3 Evaluation metrics

The biometric performance is described by the *false rejection rate* (FRR) and *false acceptance rate* (FAR). The FRR is calculated by testing each of the test prints against the correct references. For the FAR the tests prints are matched against all references except the respective correct ones [5].

Given a specific system these values depend on the score threshold of the decision unit. To visualize the behavior of the system FAR and FRR are presented as curves over the score threshold.

The *equal error rate* (EER) is the failure rate at the FAR/FRR crossing point [3]. It is used to roughly characterize the performance of a biometric system with one number only. For the stability of the system preferably a flat gradient of the FAR/FRR curves around the EER point is important. The following result section contains FAR/FRR curves for comparison only in case their gradients differ significantly.

4. SIMULATION RESULTS

4.1 Functionality of the basic system

The basic system as described in sec. 2.1 is using a 2D correlation to determine the distance of image stripes. Fig. 3 shows the FAR/FRR curves (synthetic finger database) for an exemplary finger speed of 10cm/s for reference and test sequences. The EER is 0% and the gradient of the curves around the EER point is quite low which shows a good system stability.

Fig. 4 shows the behavior of the EERs for different test speeds given certain reference speeds. As a rule, it can be observed that the EER is lowest (between 0% and 3%) if test and reference finger speed roughly correspond to each other. This is mainly due to the speed dependant image distortions. Since the finger speed of a specific user normally does not show extreme variations, the recognition performance should be about in the optimal range for every user (EER < 3%). If a wide range of finger speeds is expected, a high reference speed should be

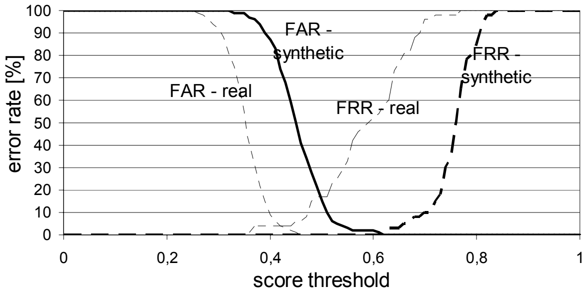

Figure 3: FAR/FRR curves for the base system.

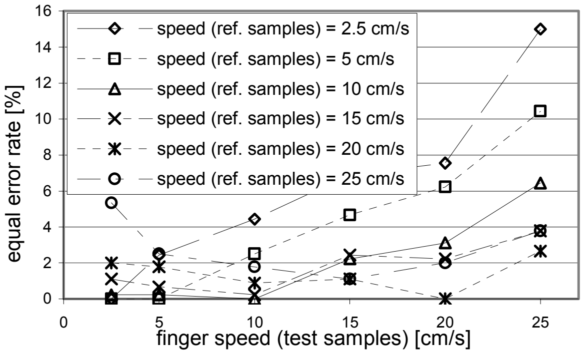

Figure 4: EER curves of the base system for different finger sweeping speeds.

chosen (e.g. the 25cm/s curve is clearly under 3% EER for a test speed range of 5-20cm/s).

Fig. 5 visualizes the sensitivity of the base approach to finger rotation (at a speed of 10cm/s). Since the individual image stripes are quite narrow, the overlap area of test and reference stripes decreases very fast with increasing angles. Additionally, the 2D correlation does not compensate for rotation. But obviously the loss in recognition rate is less than expected: up to 4 degrees rotation the difference in EER remains under 3%. Even without further algorithmic improvements this is robust enough for practical usage, especially if an appropriate finger guidance is applied.

4.2 Comparison to two stage approach

For comparison, the conventional two-stage system was evaluated using the synthetic database. The system consisted of a sophisticated prototype reconstructor together with a commercial state-of-the-art minutiae-based area fingerprint recognition software. Since the reconstructor compensates for the distortions caused by the different finger speeds, fig. 6 does not show a characteristical minimum for equal test and reference finger speeds. Up to 10cm/s the average EER is about 4% which is clearly above the 0-3% of the one-stage

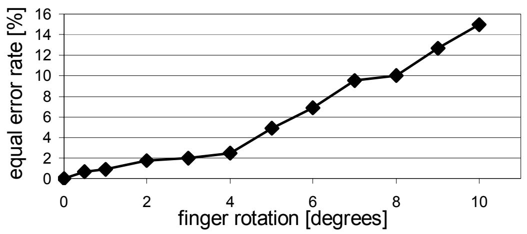

Figure 5: EER over finger rotation for the base system.

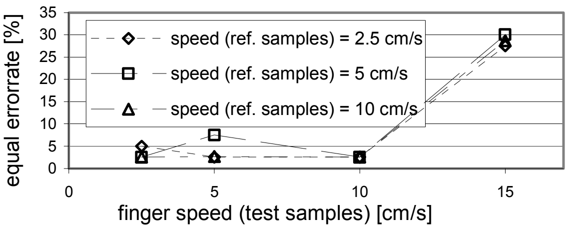

Figure 6: EER over finger speed for two-stage approach**.**

approach. If the speed exceeds the limit of 13cm/s, consecutive image stripes do not overlap any more. For that reason the EER of the two-stage system goes up to about 29% at 15cm/s whereas the one-stage system remains under 4% for up to the tested 25cm/s.

The comparison demonstrates the superiority of the two-stage approach especially but not only for higher finger speeds. Taking into account that the two-stage system already consists of highly optimized components the difference is even more significant.

4.3 Results for redundancy reducing algorithms

Table 1 shows the EERs and execution times for a typical match (on a 500MHz PIII CPU) of the redundancy reducing algorithms described in sec. 2.2 compared to the base approach of sec. 2.1 (synthetic database, 10cm/s).

As expected, the execution time of 180s for the 2D correlation based algorithm is intolerably slow. The execution time is reduced considerably down to 8s for the 1D correlation and even to 2s for the DFT features. On the other hand, the EER is increasing up to about 7% for the DFT.

The results demonstrate that the one-stage approach is feasible for practical use. Since many other features are suitable for image stripe description, there is still much potential for further optimization.

4.4 Recognition with real fingers

Fig. 3 also contains the curves for the real fingerprint database which implicitly contains all the variations of sec.

	computing time [s]	EER [%]
2D correlation	180	0.0
1D correlation	8	5.0
DFT	2	6.7

Table 1: computing times and EERs for different redundancy reducing approaches.

4.1 (plus a certain degree of smear due to finger humidity, s. fig. 2). Consequently, the EER moves up to about 4% and the steeper gradient of the FAR/FRR curves makes the adjustment of the score threshold slightly more difficult (especially on the FAR side). However, the results document that the new approach can be successfully applied on real fingerprint data.

5. CONCLUSIONS

A new approach for the direct matching of image stripes provided by fingerprint sweep sensors was presented. Although the system is still in an early prototyping state, it could be proven that it has a better performance than the conventional two-stage approach based on image reconstruction. Especially, the direct matching has no inherent restrictions for the finger sweeping speed.

First results based on simple feature extraction methods imply, that there is enough potential to optimize the system for the practical deployment in embedded systems.

6. REFERENCES

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