MEMORY-EFFICIENT FINGERPRINT VERIFICATION

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ABSTRACT

Fingerprint recognition and verification are often based on local fingerprint features, usually ridge endings or terminations, also called minutiae. By exploiting the structural uniqueness of the image region around a minutia, the fingerprint recognition performance can be significantly enhanced.

However, for most fingerprint images the number of minutia image regions (MIR's) becomes dramatically large, which imposes - especially for embedded systems - an enormous memory requirement. Therefore, we are investigating different algorithms for compression of minutia regions. The requirement for these algorithms is to achieve a high compression rate (about 20) with minimum loss in the matching performance of minutia image region matching. In this paper we investigate the matching performance for compression algorithms based on the Principal Component and the wavelet transformation. The matching results are presented in form of normalized ROC curves and interpreted in terms of compression rates and the MIR dimension.

1. INTRODUCTION

Fingerprint analysis is one of the most widespread methods among biometric identification techniques [1, 2, 3]. Fingerprints possess characteristic individual features and based on these features an acceptable recognition performance can be achieved for many applications. However, there exist many high-security applications (for example Internet transactions and banking) where false acceptance or rejection rates are extremely critical and recognition error rates must be improved.

Fingerprint matching deals with the problem of comparing an unknown fingerprint (request image) to a large set of known fingerprints (reference images) from a database. The comparison is based on matching various fingerprint features, which can be global or local structures. Typical local structures are ridge endings and bifurcations [4]. A common technique is to match the position and type of these specific locations of the request and reference fingerprints.

In this paper we present a novel method with the objective to increase the overall recognition performance. We consider within the matching process not only the minutiae position and type information, but also the local gray-value pattern around minutiae (i. e., Minutia Image Regions, MIR's) are compared. Since each MIR is structurally unique, matching of MIR's can increase the robustness of the recognition process. A similar concept has been recently proposed by Prabhakar et al. by using minutia spatial neighborhoods for minutia verification [5].

Since the MIR's require a considerable amount of memory, our secondary objective is to devise a technique to store the data efficiently. A lot of research has been dedicated to fingerprint compression [3, 6, 7], however, compression of MIR's has not been considered before.

The outline of this paper consists of two principal parts: we first present the Principal Component and wavelet compression techniques in regard to MIR compression and illustrate the effects of compression losses; the second part describes in detail the analysis of the MIR recognition performance as a function of the MIR size and the compression rate for the two different compression techniques.

2. COMPRESSION AND MATCHING OF MINUTIA IMAGE REGIONS

Our primary objective is to obtain the optimum matching performance for the problem of MIR matching. Under optimum performance we understand a system yielding the highest similarity measure for MIR's containing the same structure and having the best capability to distinguish between MIR's containing different structures.

Matching and compression of MIR's are characterized by two parameters, the compression rate and the size of the MIR's (see Fig. 1).

On one hand we would like to have a large MIR in order to increase the quality of matching. On the other hand

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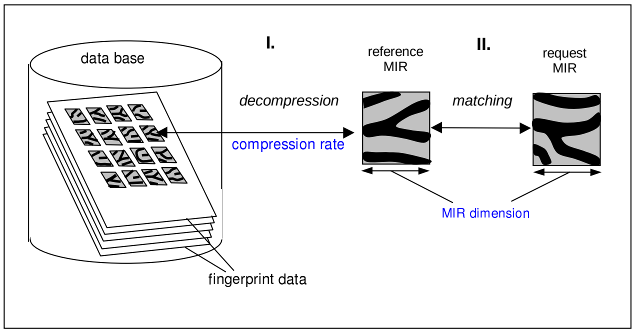

Fig. 1. The matching process with two independent subprocesses with one parameter.

a large MIR requires a higher compression rate leading to a decrease in the match performance. Therefore, we are looking for an optimal trade-off on these parameters.

3. APPLIED COMPRESSION TECHNIQUES

3.1. The Principal Component transformation

Based on the significant similarity between the MIR's we apply a transformation which reduces the correlation between MIR's. The Principal Component Transformation (PCT) is the optimal linear transform. This transformation leads to a reduction of the feature space, where information becomes concentrated in only a few of the transform coefficients [8]. A similar approach is described in [9] using the PC transformation for dimensionality reduction of minutia neighborhoods.

3.2. The discrete wavelet transform

MIR compression was also performed by using the discrete wavelet transform[1]. Image noise and certain fingerprint features (such as sweat pores) have high spatial frequency. In the wavelet transform these features appear in the detail images. These detail images can be quantized at a coarser level resulting in data reduction.

Due to the small image size of our MIR data, the wavelet transform was restricted to one level. To reduce the image data significantly, we neglected all the detail images, only the approximation image was quantized to various extents.

4. RESULTS AND DISCUSSION

The MIR's of our database were first compressed, subsequently decompressed and matched against each other. The matching was based on the cross-correlation scheme by calculating the gray level correlation between image pairs as described in [10] in detail. Our objective was to analyze, how compression loss affects the MIR matching performance.

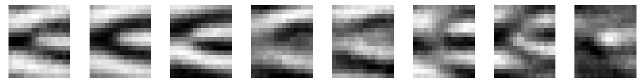

Fig. 2. The first eight eigenvectors (eigenminutiae).

Our database has been created by extracting MIR's from 30 fingerprint images. To evaluate the PCT compression and subsequent matching, the database (consisting of 560 MIR's) was split into a training and an evaluation set. The evaluation set was fully independent from the training set, since it did not contain MIR's related to the training set.

A MIR-specific eigenspace was derived from the PC transformation of the training set and a reduced representation was achieved by projecting the images of the evaluation set into this eigenspace [11]. The first eight eigenvectors (eigenminutiae) obtained from the PC transformation are displayed in Fig. 2. The very first eigenminutia images resemble the most common minutia structure.

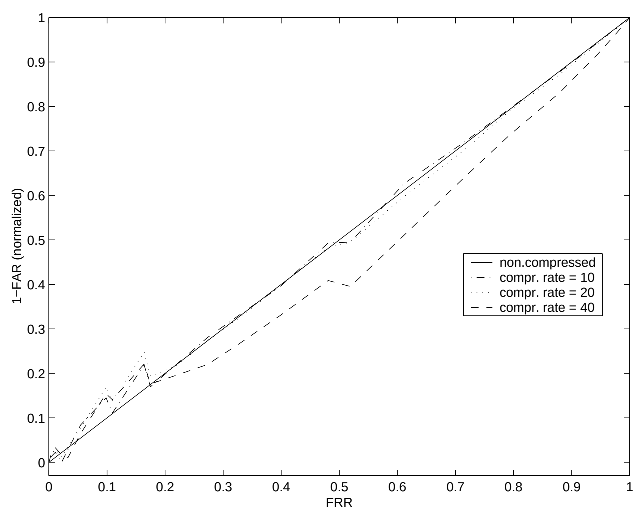

Fig. 3. Normalized ROC curves obtained from MIR matching (size: 16x16 pixels) for PCT-compressed and decompressed MIR's. Normalization was performed with the ROC curve of the non-compressed data (shown as straight line) as reference curve. For a better visibility deviations from the reference curve are magnified by a factor of 5.

The compression rate dependence of the MIR matching performance was considered for using PCT compression. PC compression of various compression rates (10, 20 and 40) was applied to the MIR's of the evaluation set (MIR size

[1]DCT yields inferior results, which are, therefore, not presented.

was 16x16 pixels). Furthermore, for an automatic minutia extraction step minutia positions within the MIR images can only be determined with an accuracy of several pixels. Therefore, they are sometimes positioned slightly off the MIR center. To localize minutiae of different positions, the matching algorithm included a translational displacement of the images by ± 5 pixels. The obtained match scores are displayed in form of normalized Receiver Operating Characteristic (ROC) curves in Fig. 3.

From the obtained match scores the False acceptance rate (FAR) and False rejection rate (FRR) were computed. These two quantities give the fraction of times the system incorrectly accepts (FAR) or rejects (FRR) two fingerprints for a given match score. FAR and FRR curves were combined to generate a normalized ROC curve. Normalization was performed relative to the ROC curve of uncompressed data. Additionally, the deviations were scaled for better visibility. The normalized ROC curve shows the trade-off between sensitivity and specificity of the MIR matching process. The further a curve is above (below) the diagonal the higher ist the improvement (deterioration) with respect to the matching performance on uncompressed MIR's.

For compression rates of 10 and 20 the matching performance does not vary or is slightly better than that for non-compressed MIR matching. We attribute this result to the fact, that the PC compression removes high-frequency components from the image, merely the fundamental minutia structure remains and matching against other MIR's yields an improved match score. At a compression rate of 40 the decompressed MIR starts to resemble the generic minutia structure and because of the loss of specificity the matching performance deteriorates.

Compression using the wavelet transform was performed on MIR's of 16x16 pixels by using a quadrature mirror filter of length 8 [12]. Quantization was performed by using different quantization levels (6, 4 and 2 bit quantizations). The different quantizations resulted in distinct compression rates (4.6, 6.4 and 10.7, respectively).

We used a matching scheme analogously to the PC transform matching. Matching of the wavelet-compressed and decompressed MIR's consisted of matching each MIR against the entire data set of our database. Matching results are shown in terms of normalized ROC curves in Fig. 4.

Matching of the wavelet transform-compressed MIR's reveals that the matching performance changes only slightly for a compression rate up to 10, but becomes significantly worse at compression rates larger than 10. Higher compression rates - due to the restricted number of decomposition levels - were not available.

When comparing this result to those obtained by the PC transform-compressed MIR's, we find, that the PC transformation produces stable matching performance at higher compression rates than the wavelet transform.

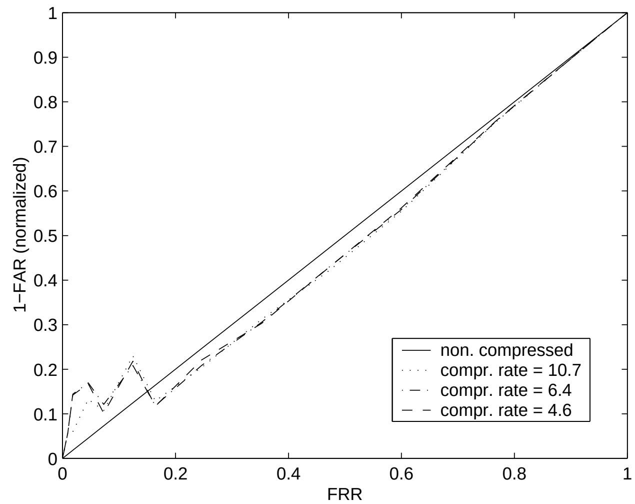

Fig. 4. Normalized ROC curves obtained from MIR matching (size 16x16 pixels) for wavelet-compressed and decompressed MIR's. Normalization was performed with the ROC curve of the noncompressed data (shown as straight line) as reference curve. For a better visibility deviations from the reference curve are magnified by a factor of 10.

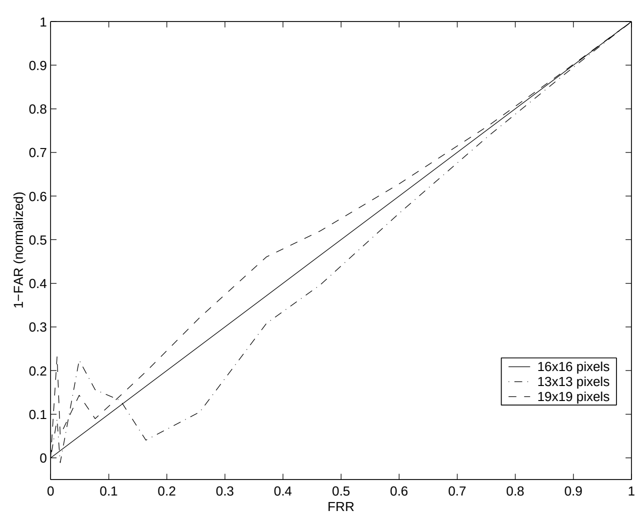

Fig. 5. Normalized ROC curves obtained from matching of non-compressed MIR's of different sizes (13x13, 16x16, and 19x19 pixels). Normalization was performed with the ROC curve of MIR data of size 16x16 (shown as straight line) as reference curve. For a better visibility deviations from the reference curve are magnified by a factor of 10.

The MIR size-dependence of the MIR matching performance was investigated. MIR's of three different sizes (13x13, 16x16, and 19x19 pixels) were matched without compression using the same matching procedure as the previous experiments. The obtained match scores are displayed in form of a normalized ROC curve in Fig. 5.

The size-dependence of the matching performance shows a marked variation. Matching of the small-sized (13x13 pixels) regions yields a significantly inferior result compared to the matching performance of large-sized regions. This performance drop is attributed to the fact that small-sized MIR's contain less structure (due to a given ridge-ridge frequency) and thus posses less structural specificity.

The computational costs associated with the two compression methods were estimated by the number of floating point operations. To perform the PC compression, it takes about 1.5 times more floating point operations than for the wavelet compression. Computational costs relative to decompression are even higher, about 2.5 times more for PCT. Note that these are figures reported by Matlab algorithms. Optimization of the code may reduce the number of operations significantly.

5. CONCLUSIONS

The main objective of this paper is to increase the overall fingerprint recognition rate by using additional information, minutia image regions in the matching process. A novel scheme of compression, decompression and subsequent matching of MIR's is considered.

For a reduced representation of the MIR's we compare two techniques, the PCT and the wavelet transform methods in terms of the matching performance for decompressed images. We find that the PC transformation compression and decompression yields stable MIR matching performance up to high (20) compression rates, whereas the wavelet transform matching shows a matching performance drop already at a compression rate of 10.

The MIR size-dependence of the matching performance reveals, that size is also a crucial factor accounting for the MIR specificity. With decreasing MIR size minutia structural information disappears and differences between distinct MIR's vanish.

In the near future experiments on a separate representation of MIR's according minutia type will be carried out to achieve more efficient compression of the MIR's. Such a representation migh be based on multiple eigenspaces (multiple PCA [13]) generated for each minutia type.

6. REFERENCES

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