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Fikret Erçal
Missouri University of Science and Technology, ercal@mst.edu

M. Gokmen

Ilker Ersoy

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Ilker Ersoy, Fikret Ercal

Department of Computer Science
University of Missouri-Rolla
Rolla, MO, USA
{ersoy,ercal}@umr.edu

Muhittin Gökmen

Department of Computer Engineering
Istanbul Technical University
Istanbul, Turkey
gokmen@cs.itu.edu.tr

ABSTRACT

We propose a new fingerprint image compression scheme based on the *hybrid model* of image. Our scheme uses the essential steps of a typical automated fingerprint identification system (AFIS) such as enhancement, binarization and thinning to encode fingerprint images. The decoding process is based on reconstructing a hybrid surface[9] by using the gray values on ridges and valleys. In this compression scheme, the ridge skeleton is coded efficiently by using *differential chain codes*. Valley skeleton is derived from ridge skeleton and the gray values along the ridge and valley skeletons are encoded using discrete cosine transform. The error between original and replica is also encoded to increase quality. One advantage of our approach is that original features such as end points and bifurcation points can be extracted directly from compressed image even for a very high compression ratio. Another advantage is that the proposed scheme can be integrated to a typical AFIS easily. The algorithm has been applied to various fingerprint images, and high compression ratios like 63:1 have been obtained. A comparison to Wavelet/Scalar Quantization (WSQ) has been also made.

1. INTRODUCTION

Compression of fingerprints is an essential step in automated fingerprint identification systems due to the increasing number of the fingerprint records in their databases. To achieve higher compression ratios, regular structure of fingerprint images should be utilized by means of model based coding techniques [2, 6, 16].

Several different methods have been reported for fingerprint compression in the literature. They can be summarized in two categories: 1) *fingerprint data* compression techniques; which are based on extracting and compressing essential data in fingerprints like ridges and/or features. These techniques are *not* able to re-construct the fingerprint image from compressed data. Some studies in this category are Abdelmalek *et al.* [1], Chong *et al.* [6], Yamada *et al.* [16] and Costello *et al.* [7]. 2) *fingerprint image* compression techniques; which are based on image transforms tuned for fingerprint images. A few also use several vector quantization techniques [11]. The techniques in this category cannot utilize the regular structural properties of fingerprints to achieve higher compression ratios. In this category, Hopper *et al.* [10], Bradley *et al.* [4] and Brislawn *et al.* [5] studied *wavelet/scalar quantization* which is used as a standard algorithm by FBI [8]. Several other compression methods utilizing wavelets have been reported by Kasci *et al.* [12] and Sherlock *et al.* [13, 14].

In this paper we propose a model-based compression scheme which enables us to reconstruct the fingerprint image from ridge skeleton. In this approach, the compression is based on deriving ridge and valley skeletons, creating the *sparse representation* of the fingerprint image and then reconstructing the fingerprint image by using the hybrid image model [9]. Since all important features such as end points and bifurcation points can be obtained from the ridge skeleton, the compressed image always maintains these features undistorted even for very high compression ratios.

2. RIDGE AND VALLEY EXTRACTION

The unique set of features like end points and bifurcation points are extracted from *ridges*, the dark curves in a fingerprint image. In our approach, the *ridge skeleton* is extracted from the ridges by binarizing and thinning the fingerprint image.

Fingerprint images are mostly degraded due to over-inking, smudging, or excessive pressure. The amount of degradation varies from region to region requiring adaptive techniques for enhancement and binarization. To overcome this varying degradation, we developed a robust adaptive thresholding algorithm. For each pixel,

the local luminance mean is calculated to determine the threshold value of that pixel. This binarized image is then thinned to obtain the ridge skeleton by using an 8-connected thinning algorithm. Figures 1-a and 1-b show a fingerprint image and its binarized image. It can be observed that degraded original image produces degraded skeleton which reduces both the compression ratio and the recognition performance. Our experiments showed that the quality and the compresssion ratio can be improved by applying very simple binary morphological operators to the binarized image.

To obtain a high compression ratio, the ridge skeleton should be coded very efficiently. We utilize an efficient *tracing algorithm* to encode ridge curves. In this algorithm, if necessary, the ridge curves are slightly modified and segmented into chains which can be coded by only two bits per chain pixel instead of three bits required in an 8-connected chain (Freeman) coding algorithm. To achieve this, the algorithm creates chains with at most 45 degrees difference between successive directions. If other possibilities arise, it starts a new chain. In this way, we utilize the regular structure of ridge skeleton while maintaining the 8-connectivity. We obtained an average compression ratio of 54:1 by applying this tracing algorithm to the test set of FBI. After morphological enhancement, this ratio increased to 63:1.

To reconstruct the gray scale image, we also utilize valley skeleton which can be derived from ridge skeleton. Since valley curves lie approximately halfway between two parallel ridge curves, there is no need to store this information. After deriving both ridge and valley skeletons, a sparse representation of the fingerprint image can be obtained by collecting gray level values along the ridges and valleys. This sparse data will be used to reconstruct the fingerprint image. Figure 1-c shows a sample sparse representation.

3. SURFACE RECONSTRUCTION USING THE HYBRID MODEL

A dense surface representation can be reconstructed from a sparse data by imposing the smoothness constraint by means of regularization theory. Given a sparse data $d(x, y)$ containing gray values on ridges and valleys, the fingerprint image $f(x, y)$ can be obtained by minimizing a hybrid energy functional [9]

$$E_{\lambda\tau}(f; x, y) = \int\int_{\Omega} \{\beta(f - d)^2 + \lambda[(1 - \tau)(f_x^2 + f_y^2) + \tau(f_{xx}^2 + 2f_{xy}^2 + f_{yy}^2)]\} dx dy, \quad (1)$$

where $\lambda > 0$ is the real-valued regularization parameter which controls the compromise between two terms and

$\tau \in [0, 1]$ is the real-valued continuity control parameter. In this functional, the first term on the right hand side is a measure of the closeness of the solution $f(x, y)$ to the data $d(x, y)$, and the second term, which is a convex combination of membrane and plate functionals[3], is a measure of the smoothness. By sweeping these two parameters in their specified range, one can generate the $\lambda\tau - space$ representation of the image. The properties of this space is studied in detail in [9].

4. RESULTS

The proposed method has been applied to various fingerprint images. First we consider the performance of the two-bit differential chain coding and compare it with standard three-bit chain coding. The proposed tracing algorithm remarkably increases the average compression ratio from 32:1 to 45:1 for clipped fingerprint images. These results are also superior to the results reported in [6] where the average compression ratio obtained by B-spline modeling is about 20:1 - 25:1 [1].

We next consider several different levels of quality in forming the sparse data on ridge and valley skeletons: *a*) by using only two fixed gray values for all pixels on ridge and valley skeletons, *b*) by encoding differences between gray values along ridge and valley chains by discrete cosine transform, *c*) by applying *case b* and also encoding the error between the original and reconstructed images.

As expected, the average compression ratio is maximum (54:1 without morphological enhancement) for *case a* where fixed gray values are used to generate ridges and valleys in sparse data. The reconstructed image is an enhanced version of the original image and it contains all information essential for classification and identification. Figure 2 compares magnified portions of a fingerprint reconstructed by the proposed method for *case a*, standard JPEG and WSQ for a compression ratio of 40:1.

In *case b*, all gray values along ridges and valleys are smoothed and the differences between consecutive pixels are encoded after having applied discrete cosine transform. Depending on the number of coefficients encoded, the compression ratio reduces to a range of 9:1 - 44:1, while providing a highly acceptable replica of the original image. The average compression ratios for this case are 28:1 (15% of DCT coefficients encoded) and 17:1 (all DCT coefficients encoded). These results are obtained by applying the proposed method to a set of 17 original fingerprint images of NIST, which, together with their corresponding WSQ-decompressed images, are used for WSQ compliance procedure. Figure 1-d

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[1]Since no specific image size has been reported, we assume that this ratio is obtained for clipped fingerprint images.

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shows a reconstructed image for 19:1 compression ratio. Although the quality of the reconstructed image is acceptable, a better image can be obtained by encoding the error between original and reconstructed images.

In *case c*, the error between original and reconstructed images are encoded by using block DCT and zigzag coding of DCT coefficients (similar to JPEG). For this case the compression ratio and the image quality is competitive to the 0.75 bpp target ratio set by FBI. Figure 3 shows magnified portions of the original and reconstructed images by proposed method and WSQ. Although NMSEs are equal, proposed method produces an image with just noticeable block artifacts due to DCT. Table 1 shows compression results of WSQ and proposed method (*case c*) applied to FBI test set.

5. DISCUSSION AND FUTURE WORK

In this paper, we have described a model-based approach for compressing fingerprint images which is based on a compact representation of the structural properties of a fingerprint. Reconstruction is achieved by using a *hybrid image model*. We have also suggested an implementation for this approach which uses a special tracing algorithm for ridge curves and discrete cosine transform for gray level values. Different implementations can be developed for obtaining better results. Average compression ratio of our implementation depends on the number of ridge chains and pixels. To improve the quality and the compression, ridges can be enhanced and simplified prior to encoding to eliminate false features and excessive data.

The main contribution of this work is to provide a new approach which exploits the structural properties of fingerprint images to achieve higher compression ratios and good quality images. A natural result of this approach is that the original structural properties such as the number and relative locations of ridge endings and bifurcations are well preserved, i.e., they are not affected by reconstruction quality. They can be easily extracted from compressed data without reconstruction. We also showed that the quality of reconstruction is competitive to existing methods. Another contribution of this approach is to unify the advantages of both *fingerprint data compression* and *fingerprint image compression* algorithms existing in the literature.

The computational overhead of the compression part in *case a* and *case b* dramatically reduces when integrated to an AFIS because this part uses most of the preprocessing steps of a typical AFIS. For *case c*, compression part involves decompression too, because the error between original and reconstructed image is to be encoded. The performance of decompression part

depends on the implementation of reconstruction process. Since this process involves many iterations it becomes the bottleneck of decompression. To accelerate this process, multigrid methods [15] can be employed. Multigrid reconstruction methods produce images in faster and less number of iterations.

Steps of the future work derived from this discussion can be summarized as follows: preprocessing methods should be improved to simplify the ridge skeleton for obtaining higher compression ratio. Suitable transforms which can represent small changes (as in the error image) better than DCT may be used to compress error image futher. And finally, to overcome the bottleneck in decompression part, faster algorithms including multigrid method need to be developed.

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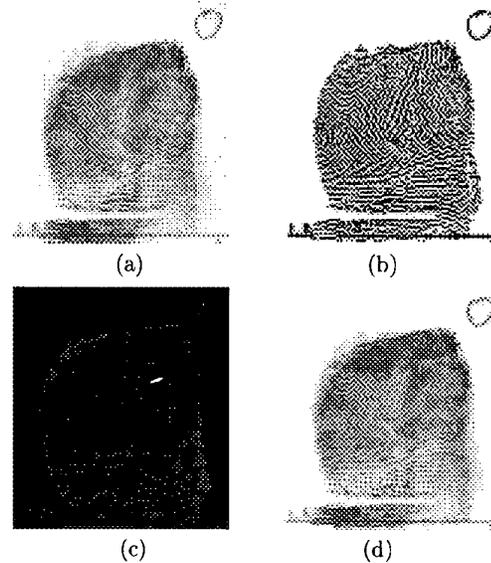
(a)   (b)

(c)   (d)

Figure 1: a) Original fingerprint image, b) binary image, c) sparse representation, d) reconstructed image (*case b*) ratio=19:1, NMSE=0.00447.
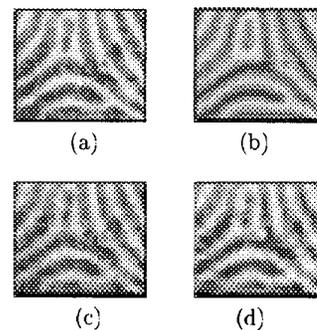

(a)   (b)

(c)   (d)

Figure 2: Magnified fingerprints for ratio 40:1; a) original fingerprint image and reconstructed fingerprints from b) the proposed method (*case a*), c) JPEG, and d) WSQ.

Table 1: *case c* : compression results for equal distortion.

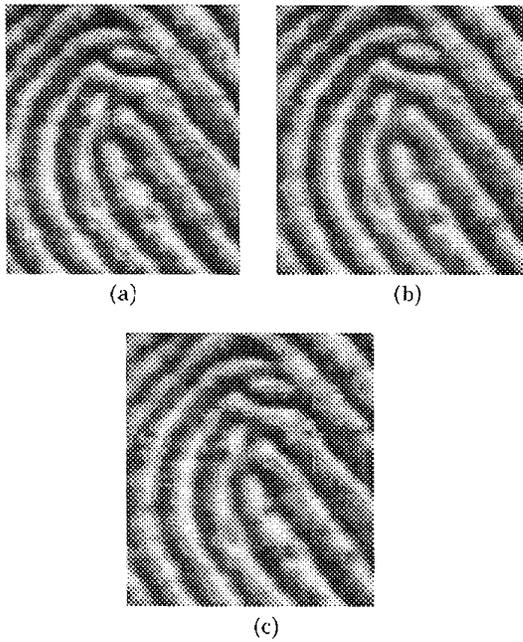| image	WSQ ratio	method ratio	image	WSQ ratio	method ratio
01	12.7	10.8	10	11.8	8.7
02	15.2	12.8	11	12.0	10.1
03	18.2	15.5	12	12.2	10.5
04	18.6	16.2	13	13.9	10.5
05	15.9	13.3	14	13.0	8.5
06	16.0	13.6	15	12.3	9.5
07	11.4	8.8	16	15.1	11.6
08	17.9	15.6	17	12.6	9.7
09	14.0	10.9	**Avg.**	**14.3**	**11.6**

(a)

(b)

(c)

Figure 3: Magnified fingerprints for NMSE=0.00033; a) Original fingerprint image and reconstructed fingerprints by b) the proposed method (*case c*), ratio=11.6:1, c) WSQ, ratio=15:1.