Fingerprint Compression General Rules Based on Lossy Representation

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Abstract- *A new fingerprint compression algorithm situated on sparse representation is introduced. Obtaining an over complete dictionary from a set of fingerprint patches allows for us to represent them as a sparse linear combo of dictionary atoms. Within the algorithm, we first construct a dictionary for predefined fingerprint image patches. For a new given fingerprint pix, symbolize its patches in step with the dictionary by way of computing l0-minimization and then quantize and encode the representation. In this paper, we do not forget the effect of various factors on compression results. Three groups of fingerprint photos are established.*

The experiments display that our algorithm is efficient in comparison with a few competing compression methods (JPEG, JPEG 2000, and WSQ), peculiarly at excessive compression ratios. The experiments additionally illustrate that the proposed algorithm is potent to extract trivia.

I. INTRODUCTION

Awareness of men and women by the use of biometric traitsisan major science within the society, considering the fact that biometric identifiers can't be shared they usually intrinsically symbolize the individual's bodily identification. Amongst many biometric recognition technologies, fingerprint awareness is very wellknown for personal identification as a result of the uniqueness, universality, collectability and invariance [1].

Huge volumes of fingerprint are collected and stored every day in a wide range of applications, together with forensics and entry control. In 1995, the size of the FBI fingerprint card archive contained over 200 million objects and archive dimension used to be growing at the cost of 30 000 to 50 000 new playing cards per day [1]. Colossal volume of knowledge consume the amount of reminiscence.

Fingerprint photo compression is a key process to resolve the drawback. Frequently, compression technologies can also be classed into lossless and lossy. Lossless compression enables the designated normal pictures to be reconstructed from the compressed knowledge. Lossless compression applied sciences are used in instances where it's most important that the original and the decompressed data are same. Averting distortion limits their compression effectively. When used in image compression theplace mild distortion is acceptable, lossless compression applied sciences are traditionally employed in the output coefficients of lossy compression.

Lossy compression applied sciences on the whole develop into an snapshot into a different domain, quantize and encode its coefficients. For the period of the final three a long time, grow to be-centered photo compression technologies were greatly researched and some necessities have appeared. Two most usual options of transformation are the Discrete Cosine turn into (DCT) [2] and the Discrete Wavelet grow to be (DWT) [3].

The DCT-established encoder will also be concept of as compression of a move of eight × 8 small block of snap shots. This turn into has been adopted in JPEG [4]. The JPEG compression scheme has many advantages such as simplicity, universality and availability. Nevertheless, it has a foul efficiency at low bit-charges quite often considering of the underlying block-centered DCT scheme.

Consequently, as early as 1995, the JPEG-committee started to improve a brand new wavelet-situated compression typical for nonetheless photographs, namely JPEG 2000 [5],[6]. The DWT-founded algorithms incorporate three steps: a DWT computation of the normalized picture, quantization of the DWT coefficients and lossless coding of the quantized coefficients. The element can bedis covered in [7] and [8]. When put next with JPEG, JPEG 2000 presents many points that help scalable and interactive access to colossal-sized photograph. It also allows extraction of extraordinary resolutions, pixel fidelities, regions of interest , components and and many others. There are a couple of different DWT-based algorithms, comparable to Set Partitioning in Hierarchical trees (SPIHT) Algorithm [9]. The above algorithms are for basic image compression.

Unique at fingerprint portraits, there are detailed compression algorithms. Probably the most common is

Wavelet Scalar Quantization (WSQ). It grew to be the FBI normal for the compression of 500 dpi fingerprint photos [7]. Motivated by using theWSQ algorithm, just a few wavelet packet established fingerprint compression schemes had been developed. Moreover to WSQ, there are other algorithms for fingerprint compression, such as Contour let become (CT) [10].

In most occasions, the analysis of compression efficiency of the algorithms is restrained to height signal to Noise Ratio (PSNR) computation. The results on specific fingerprint matching or awareness should not investigated. In this paper, we will take it into consideration. In most computerized Fingerprint identification system (AFIS), the foremost characteristic used to compare two fingerprint pictures are trivia (ridges endings and bifurcations). As a consequence, the change of the minutiae between pre- and publish-compression is considered within the paper.

This paper is organized as follows: part II summarizes the associated works and gives some thoughts on the sparse representation; the model of the sparse representation and the algorithms for the model are installed in section III; the small print of fingerprint compression centered on sparse representation is given in section IV; experiments will accept in part V; ultimately, we draw a quick conclusion and the longer term work.

II.RELATED WORKS AND SOME THOUGHTS

The field of sparse representation is relatively young. Early signs of its core ideas appeared in a pioneering work [11].In that paper, the authors introduced the concept of dictionaries and put forward some of the core ideas which later became essential in the field such as a greedy pursuit technique. Thereafter, S. S. Chen, D. Donoho and M. Saunders [12] introduced another pursuit technique which used $l1$-norm for sparse. It is surprising that the proper solution often could be obtained by solving a convex programming task. Since the two seminal works, researchers have contributed a great deal in the field. The activity in this field is spread over various disciplines. There are already many successful applications in variousfields, such as face recognition [13], image denoising [14], object detection [15] and super-resolution image reconstruction [16].

In paper [13], the authors proposed a general classification algorithm for object recognition based on a sparse representation computed by $l1$-minimization. On one hand, the algorithm based on sparse representation has a better performance than other algorithms such as nearest neighbor, nearest subspace and linear SVM; on the other hand, the new framework provided new insights into face recognition: with sparsity properly harnessed, the choice of features becomes less important than the number of features. Indeed, this phenomenon is common in the fields of sparse representation. It doesn't only exist in the face recognition, but also appears in other situations.

In paper [14], based on sparse and redundant representations on over-complete dictionary, the authors designed an algorithm that could remove the zero-mean white and homogeneous Gaussian additive noise from a given image. In this paper, we can see that the content of the dictionary is of importance. The importance is embodied in two aspects. On one hand, the dictionary should correctly reflect the content of the images; on the other hand, the dictionary is large enough that the given image can be represented sparsely. These two points are absolutely vital for the methods based on sparse representation. Sparse representation has already some applications in image compression [17], [18]. In paper [17], the experiments show that the proposed algorithm has good performance.

However, its compression efficiency is consistently lower than JPEG 2000's. If more general natural images are tested, this phenomenon will be more obvious that the compression efficiency is lower than the state-of-the-art compression technologies. In paper [18], the experiments show success compared to several known compression techniques. However, the authors emphasize that an essential pre-process stage for this method is an image alignment procedure. It is hard to do in the practical application. There are other algorithms [19]–[21] for fingerprint image compression under a linear model assumption. In paper [20], [21], the authors showed how to exploit the datadependent nature of Independent Component Analysis (ICA) to compression special images (face and fingerprint images).
The experiments of the two papers suggested that, for special class, it was not worth to use over-complete dictionaries. In this paper, we show the fingerprint images can be compressed better under an over-complete dictionary if it is properly constructed. In paper [19], the authors proposed an algorithm of fingerprint compression based on Nonnegative,Matrix Factorization (NMF) [22], [23]. Although NMF has some successful applications, it also has shortcomings. In some cases, non-negativity is not necessary. For example, in the image compression, what is considered is how to reduce the difference between pre- and post-compression rather than non-negativity.

III. THE MODEL AND ALGORITHMS OF SPARSEREPRESENTATION

A. The Model of Sparse Representation

Given $A = [a1, a2, . . . , aN] \in RM\times N$, any new sample $y \in RM\times 1$, is assumed to be represented as a linear combination of few columns from the dictionary A, as shown in formula (1).

This is the only prior knowledge about the dictionary in our algorithm. Later, we will see the property can be ensured by constructing the dictionary properly.

$y = Ax$ (1) where $y \in RM\times 1$, $A \in RM\times N$ and $x = [x1, x2, . . . ,xN]T \in RN\times 1$.

Obviously, the system $y = Ax$ is underdetermined when $M < N$. Therefore, its solution is not unique. According to the assumption, the representation is sparse. A proper solution can be obtained by solving the following optimization problem:
$(l0)$:min _x_0 $s.t.$ $Ax = y$ (2)

Solution of the optimization problem is expected to be very sparse, namely, _x_0 _ N. The notation _x_0 counts the nonzero entries in x. Actually it is not a norm. However, without ambiguity, we still call it $l0$-norm. In fact, the compression of y can be achieved by compressing x. First, record the locations of its non-zero entries and their magnitudes. Second, quantize and encode the records. This is what we will do. Next, techniques for solving the optimization problem are given.

B. Sparse Solution by Greedy Algorithm

Researchers' first thought is to solve the optimization problem $l0$ directly. However, the problem of finding the sparsest solution of the system (2) is NP-hard [24]. The Matching Pursuit (MP) [25] because of its simplicity and efficiency is often used to approximately solve the $l0$ problem. Many variants of the algorithm are available, offering improvements either in accuracy or/and in complexity. Although the theoretical analysis of these algorithms is difficult, experiments show that they behave quite well when the number of non-zero entries is low.

C. Sparse Solution by l1-Minimization

It is a natural idea that the optimization problem (2) can be approximated by solving the following optimization problem:

$(l\ p)$: min $||x||pps.t.$ $Ax = y$ (3) where $p > 0$ and $||x||pp$ $= ||ni=1|xi\ |p$.

Obviously, the smaller p is, the closer the solutions of the two optimization problems $l0$ and $l\ p$ are, asillustrated in Fig. 1. This is because the magnitude of x is not important when p is very small. What does matter is whether x is equal to 0 or not. Therefore, p is theoretically chosen as small as possible. However, the optimization problem (3) is not convex if $0 < p < 1$. It makes $p = 1$ the most ideal situation, namely, the following problems.
$(l1)$:min $||x//1$ $s.t.$ $Ax = y$ (4)

Recent developments in the field of sparse representation and compressed sensing [26]–[30] reveal that the solution of the optimization problem (4) is approximately equal to the solution of the optimization problem (2) if the optimal solutionis sparse enough.

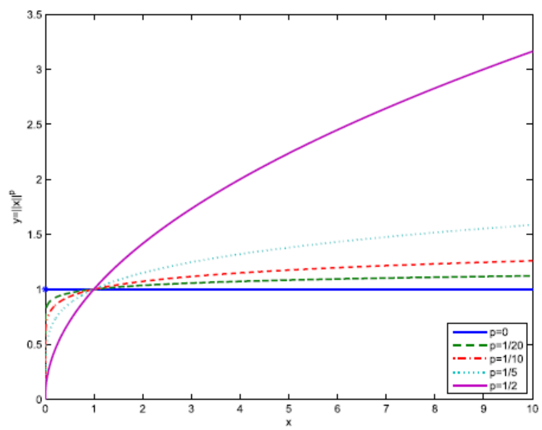


Fig. 1.The behavior of $||x||p$ for various values of p. As p tends to zero,$||x||p$ approaches the $l0$-norm.

The problem (4) can be effectively solved by linear programming methods. In addition to the above algorithms, there are otheralgorithms [31], [32] for the problems (2) or (4). There are also several well-developed software packages that handle this problem, which are freely shared on the web. These include $l1$-magic by Candes and Romberg, Sparselab managed by David Donoho, SparCo by Michael Friedlander and others.

IV. FINGERPRINT COMPRESSION BASED ON REPRESENTATION

In this section, we give the details about how to use sparse representation to compress fingerprint images. The part includes construction of the dictionary, compression of a given fingerprint, quantization and coding and analysis of the algorithm complexity.

In the preceding paragraphs, it is mentioned that the size of the dictionary may be too large when it contains as much information as possible. Therefore, to obtain a dictionary with a modest size, the preprocessing is indispensable. Influenced by transformation, rotation and noise, the fingerprints of the same finger may look very different. What we first think is that each fingerprint image is pre-aligned, independently of the others. The most common pre-alignment technique is to translate and rotate the fingerprint according to the position of the core point. Unfortunately, reliable detection of the core is very difficult in fingerprint images with poor quality. Even if the core is correctly detected, the size of the dictionary may be overlarge because the size of a whole fingerprint image is too large. Compared with general natural images, the fingerprint images have simpler structure. They are only composed of ridges and valleys. In the local regions, they look the same.

Therefore, to solve these two problems, the whole image is sliced into square and non-overlapping small patches. For these small patches, there are no problems about transformation and rotation. The size of the dictionary is not too large because the small blocks are relatively smaller.

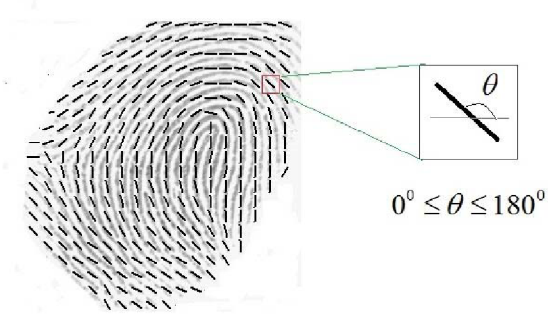


Fig. 2. A fingerprint image with its corresponding orientation image computed over a square-meshed grid. Each element denotes the local orientation of the fingerprint ridges.

Algorithm 1 Fingerprint Compression Based on Sparse Representation

1. **For a given fingerprint, slice into small patches.**
2. **for each patch, its mean is calculated and subtracted from the patch.**
3. **For each patch, solve the l^0–minimization problem by MP method.**
4. **Those coefficients whose absolute value are less than a given threshold are treated as zero. Record the remaining coefficients and their locations.**
5. **output the compressed stream.**

Algorithm 1 summaries the complete compression process. The compressed stream doesn't include the dictionary and the information about the models. It consists solely of the encoding of the atom number of each patch, the mean value of each patch, the coefficients plus the indexes. In practice, only the compressed stream needs to be transmitted to restore the fingerprint. In both encoder and the decoder, the dictionary, the quantization tables of the coefficients and the statistic tables for arithmetic coding need to be stored. In our experiments, this leads to less than 6 Mbytes. The compression rate equals the ratio of the size of original image and that of the compressed stream.

Experiment Results on DATABASE 4: Fig. 10 and Table IV show the average performances of the proposed algorithms, JPEG, JPEG 2000 and WSQ. The results on

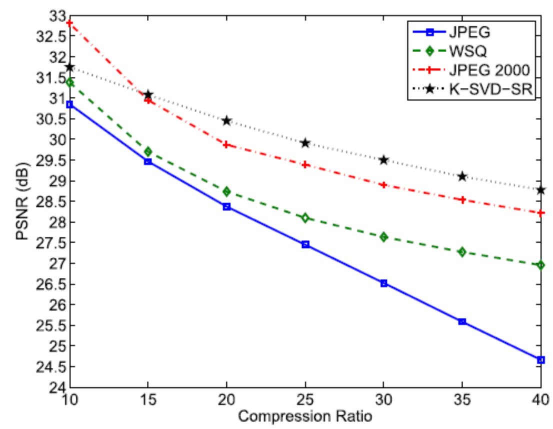


Fig. 10.Average performance of the proposed algorithms as well as JPEG, JPEG 2000 and WSQ algorithms, at various compression ratios, on DATABASE 2.

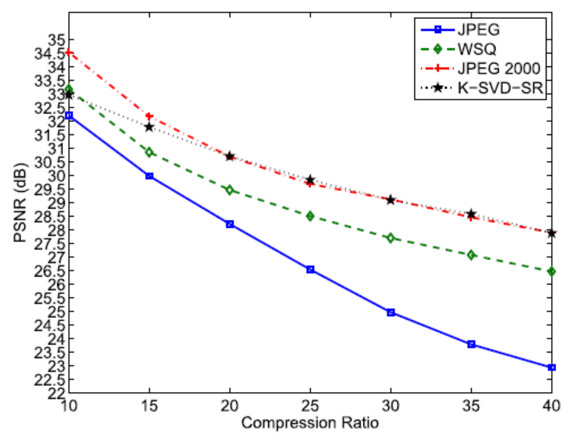


Fig. 11.Average performance of the proposed algorithms as well asJPEG, JPEG 2000 and WSQ algorithms, at various compression ratios, on DATABASE 3.

DATABASE2 are roughly consistent with the results on DATABASE 1. Compared with JPEG and WSQ, our proposed algorithm's PSNR and JPEG 2000's PSNR are consistently higher. At compression ratio 10 :1, JPEG2000 works better than ours, too. At compression ratio 15 :1, the performance of our method is as good as that of JPEG 2000. At higher compression ratio, our algorithm outperforms the JPEG 2000. From the figure, we can see that the curve of our algorithm is the most flat. This means the rate of decay of our algorithm's PSNR is the slowest as the compression ratio increases.

TABLE-I

The mean values and the variances of the difference between the real compression ratios and the given compression ratios. for each grid, the left is the mean value and the right is the variance

Compression Ratio	10	15	20	25
DATABASE1	1.07,1.08	027,0.004	0.52,0.19	0.86,0.58
DATABASE2	0.47,0.17	0.38,0.37	0.68,0.24	0.71,0.31
DATABASE3	0.30,0.08	0.38,0.10	0.55,0.13	1.22,1.31

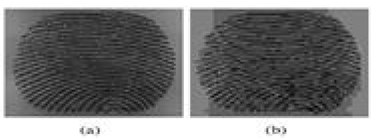
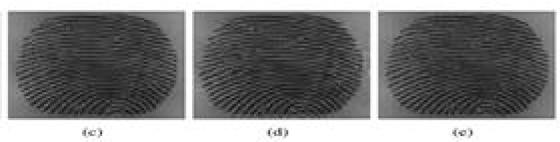


Fig: (a) Original image with size 300 × 300, (b) JPEG



(c) JPEG 2000, (d) WSQ, (e) the proposed method at compression ratios 40 :1.

V. CONCLUSION

A new compression algorithm adapted to fingerprint images is introduced. Despite the simplicity of our proposed algorithms, they compare favorably with existing more sophisticated algorithms, especially at high compression ratios. Due to the block-by-block processing mechanism, however, the algorithm has higher complexities.

The experiments show that the block effect of our algorithm is less serious than that of JPEG. We consider the effect of three different dictionaries on fingerprint compression. The experiments reflect that the dictionary obtained by the K-SVD algorithm works best. Moreover, the larger the number of the training set is, the better the compression result is. One of the main difficulties in developing compression algorithms for fingerprints resides in the need for preserving the minutiae which are used in the identification. The experiments show that our algorithm can hold most of the minutiae robustly during the compression and reconstruction. There are many intriguing questions that future work should consider. First, the features and the methods for constructing dictionaries should be thought over. Secondly, the training samples should include fingerprints with different quality ("good", "bad", "ugly"). Thirdly, the optimization algorithms for solving the sparse representation need to be investigated.

Fourthly, optimize the code to reduce complexity of our proposed method. Finally, other applications based on sparse representation for fingerprint images should be explored.

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