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AN EFFICIENT COMPRESSION ALGORITHM FOR FINGERPRINT IMAGES USING SPARSE REPRESENTATION

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ABSTRACT

Recognition of person by means of their biometric characteristics is very popular among the society. Among this, for personal identification fingerprint recognition is an important technology due to its unique structure. Human fingerprints are rich in details called minutiae. This can be used for identification marks for fingerprint verification. Large volume of fingerprint images are collected and stored day by day from a wider range of applications. Compression of data is commanding of under certain circumstances due to large amount of data transmission and efficient memory utilization.

A new and efficient fingerprint compression algorithm using sparse representation is proposed. Obtaining an over complete dictionary from a set of fingerprint patches allows us to represent them as a sparse linear combination of dictionary atoms. In the algorithm, first construct a dictionary for predefined fingerprint image patches. For a new given fingerprint images, represent its patches according to the dictionary by computing l0- minimization and then quantize and encode the coefficients and other related information using lossless coding methods. A fast Fourier filtering transformation for image post processing helped to improve the contrast ratio of the regenerated image The effect of various factors on compression results robust to extract minutiae, better PSNR, verbosity for reconstructed images and better compression ratio.

KEYWORDS: Compression; Dictionary learning; Fingerprint; Matching pursuit; Sparse coding.

INTRODUCTION

Personal identification is to associate a particular individual with an identity. It plays a critical role in our society. A wide variety of systems require reliable personal authentication schemes to either confirm or determine the identity of individuals requesting their services. In the absence of robust authentication schemes, these systems are vulnerable to the wiles of an impostor. Traditionally, passwords and ID cards have been used to restrict access to systems. The major advantages of this traditional personal identification are that

(i) They are very simple

(ii) They can be easily integrated into different systems with a low cost.

However these approaches are not based on any inherent attributes of an individual to make a personal identification thus having number of disadvantages like tokens may be lost, stolen, forgotten, or misplaced PIN may be forgotten or guessed by impostors. Security can be easily breached in these systems when a password is divulged to an unauthorized user or a card is stolen by an impostor. Further, simple passwords are easy to guess by an impostor and difficult passwords may be hard to recall by a legitimate user. Therefore they are unable to satisfy the security requirements of our electronically interconnected information society. The emergence of biometrics has addressed the problems that plague traditional verification.

In the world of computer security, biometrics refers to authentication techniques that rely on measurable physiological and individual characteristics that can be automatically verified.

Among many biometric recognition technologies, fingerprint recognition is very popular for personal identification due to the uniqueness, universality, collectability and invariance. Typical fingerprint recognition methods employ feature-based image matching, where minutiae (i.e., ridge ending and ridge bifurcation) are extracted from the registered fingerprint image and the input fingerprint image, and the number of corresponding minutiae pairings between the two images is used to recognize a valid fingerprint image. The feature-based matching provides an effective way of identification for majority of people. The minutiae based automatic identification technique first locates the minutiae point and matches their relative placement in a given finger and the stored template.

Fingerprint compression using sparse representation has been implemented. Dictionary has been formulated from a set of fingerprint patches. First construct dictionary based on predefined fingerprint patches. Every fingerprint image is going to minimize by l0 minimization algorithm. Matching pursuit is a type of sparse approximation which involves finding the best matching projections of multidimensional data onto an overcomplete dictionary D.

Compared to general natural images, the fingerprint images have simpler structure and composed of ridges and valleys, in the local regions they look the same. So the whole images are sliced into square and non-overlapping 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 smaller. The seemingly contradictive effect is achieved in a conventional optimization framework making use of gradient minimization, which can be probably controls how many non-zero gradients are resulted to approximate prominent structure in a structured sparsity management manner. Coefficients can be quantified by Lloyd's algorithm finding evenly spaced sets of points in subsets in to well saved and uniformly sized convex cells. Finally all values will be encoded using arithmetic encoding. It is a form of entropy encoding using lossless data compression. It compact favorably with existing more sophistic algorithm especially at high compression ratios.

In proposed system, new approach has been proposed. That is sparse representation in which first initial dictionary has been constructed. In this, dictionary formation case with the algorithm has been implemented via singular valued decomposition by means of k-means clustering method. It works by iteratively altering between sparse encoding. The input data based on the current dictionary and updating a in the dictionary to better fit the data. Next every image will be compressed by orthogonal matching pursuit algorithm method l0 minimization process has been implemented. MP is a type of sparse approximation which involves finding the best matching projection of multidimensional data over complete dictionary D.

This paper is arranged as follows; section II summarizes the related works. Section III shows the details of fingerprint compression based on sparse coding. Section IV draw a brief conclusion and the future work.

LITERATURE REVIEW

The field of sparse representation is relatively young. In paper [9], the authors proposed a compression technique called WSQ; FBI fingerprint compression standard (Wavelet Scalar Quantization) WSQ is also based on Wavelet packet transform [9]. It has been reported that compression ratio attained by WSQ method ranges from 10:1 to 25:1 [18].

Early signs of its core ideas appeared in a pioneering work [12]. 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 [15] 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 various fields, such as face recognition [16], image denoising, object detection [17] and super-resolution image reconstruction.

In paper[5], a Comparative Performance Analysis of JPEG 2000 vs. WSQ for Fingerprint Image Compression. The FBI Wavelet Scalar Quantization (WSQ) compression standard was developed by the US Federal Bureau of Investigation (FBI). The main advantage of WSQ-based fingerprint image compression has been its superiority in preserving the fingerprint minutiae features even at very high compression rates which standard JPEG compression techniques were unable to preserve. With the advent of JPEG 2000 image compression technique based on Wavelet transforms moving away from DCT-based methods, we have been motivated to investigate if the same advantage still persists. In this paper, we describe a set of experiments we carried out to compare the performance of WSQ with JPEG 2000. The performance analysis is based on three public databases of fingerprint images acquired using different imaging sensors. Our analysis shows that JPEG 2000 provides better compression with less impact on the overall system accuracy performance.

In Compression of Touchless Multiview Fingerprints system, investigates the comparative performance of several encoders for this data, namely WSQ, JPEG2000, H.264/AVC and MMP. WSQ encoder, which is the current compression standard for contact based fingerprints, is objectively outperformed by all others. WSQ is a format with a large degree of flexibility, The WSQ wavelet is a biorthogonal wavelet Cohen-Daubechies-Feauveu (CDF) 9-7, with a complex decomposition in 64 subbands. JPEG2000

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also based on wavelet transforms, the JPEG2000 is a lossy and lossless image coding standard lossy compression it also uses the CDF 9-7 transform, while for lossless compression it uses the CDF 5-3 transform. JPEG2000 provides better compression than the WSQ, for contact-based images, with less impact on the overall accuracy performance of a biometric system H.264/AVC is a video compression standard. Very efficient compressor for still images Minimize undesired blocking artifacts. MMP the Multidimensional Multiscale Parser algorithm (MMP), was originally proposed as a generic lossy pattern matching data compression method. AVC-I and ADC present better performance than JPEG2000 in the range of 0.5 to 1.0 bits/pixel. MMP is the most efficient algorithm for this kind of data.

In paper [16], the authors proposed a general classification algorithm for object recognition based on a sparse representation computed by *l*1-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.

Coiflet-type wavelet compression for fingerprint images [13]. Coiflet-Type wavelets and achieved to determine the most appropriate Coiflet-Type wavelet for better compression of a digitized fingerprint image and to achieve our goal Retain Energy (RE) and Number of Zeros (NZ) in percentage is determined for different Coiflet-Type wavelets at different threshold values at the fixed decomposition level 3 using wavelet and wavelet packet transform. Some wavelet families exists such as Symlets, Daubechies and Coiflets etc. and one may use different types of wavelet to compress fingerprint images or any other images. Increasing rate of RE is comparatively more than the decreasing rate of NZ higher order's Coiflet-type wavelet gives much better compression result Coiflet provides maximum RE and NZ in all Coiflet-type wavelet's. Hence we would like to say that RE and NZ are increasing by increasing order of Coiflets wavelet. Wavelet packets transform gives much better result than wavelet transform.

FINGERPRINT COMPRESSION USING SPARSE CODING

Sparse coding is the modeling of data vectors as sparse linear combinations of basic elements which is widely used in machine learning, neuroscience, signal processing, and statistics. It may focuses on the large-scale matrix factorization problem that consists of learning the basic set in order to adapt it to specific data. Variations of this problem include dictionary learning in signal processing. Here it proposes to address these tasks with a new online optimization algorithm, based on stochastic approximations, which scales up gracefully to large data sets with millions of training samples, and extends naturally to various matrix factorization formulations, making it suitable for a wide range of learning problems.

A) The Model And Algorithms – Sparse Coding

The model of sparse representation is given as, A = $[a_1, a_2, \ldots\ldots a_n] \in R^{M\times N}$, any new sample y $\in R^{M\times 1}$, is assumed to be represented as a linear combination of few columns from the dictionary A, as shown in equation 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.

$$y = Ax \qquad (1)$$

where $y \in R^{M\times 1}$, $A \in R^{M\times N}$ and $x = [x_1, x_2, \ldots\ldots x_n]^T \in R^{N\times 1}$. 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

$$(l^0) : \min \|x\|_0 \quad \text{s.t. } Ax = y \qquad (2)$$

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 *l*0-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.

Sparse solution by greedy algorithm is the first thought to solve the optimization problem *l*0 directly. However, the problem of finding the sparsest solution of the system is NP-hard [24]. The Matching Pursuit (MP), because of its simplicity and efficiency is often used to approximately solve the *l*0 problem. Many variants of the algorithm are available, offering improvements either in accuracy or in complexity.

Sparse Solution by l1-Minimization is a natural idea that the optimization problem which can be approximated by solving the following optimization problem

(l^p) : min $||x||_p^p$ s.t. Ax = y (3)

Obviously, the smaller p is, the closer the solutions of the two optimization problems $l^0$and l^p. 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

(l^1) : min $||x||_1$ s.t. Ax = y (4)

Recent developments in the field of sparse representation and compressed sensing [27] reveal that the solution of the optimization problem is approximately equal to the solution of the optimization problem if the optimal solution is sparse enough. The problem can be effectively solved by linear programming methods. In addition to the above algorithms, there are other algorithms for the optimization problems. There are also several well-developed software packages that handle this problem, which are freely shared on the web.

Algorithm 1 Fingerprint Compression Technique based on Sparse Representation [1].

1: For a given fingerprint, slice it into small Patches.

2: For each patch, its mean is calculated and subtracted from the patch.

3: For each patch, solve the l0 - minimization problem by OMP method.

4: Those coefficients whose absolute value is less than a given threshold are treated as zero. Record the remaining coefficients and their locations.

5: Encode the atom number of each patch, the mean value of each patch, and the indexes; quantize and encode the coefficients.

6: Perform fast fourier post processing transformation for the quantized image

7:Output the compressed stream.

Dictionary Creation

The dictionary will be constructed in three different ways. First, we construct a training set. Then, the dictionary is obtained from the set. Choose the whole fingerprint images, and cut them into fixed-size square patches. Given these patches after the initial screening, a greedy algorithm is employed to construct the training samples.

- The first patch is added to the dictionary, which is initially empty.
- Then we check whether the next patch is sufficiently similar to all patches in the dictionary. If yes, the next patch is tested. Otherwise, the patch is added into the dictionary. Here, the similarity measure between two patches is calculated by solving the optimization problem.

$$s(p_1, p_2) = \min_t ||\frac{p_1}{||p_1||_F^2} - t * \frac{p_2}{||p_2||_F^2}||_F^2 \quad (5)$$

where $||\bullet||_F^2$ is the Frobenius norm. p_1 and p_2 are the corresponding matrices of two patches. t, a parameter of the optimization problem (5), is a scaling factor.

- Repeat the second step until all patches have been tested.

Before the dictionary is constructed, the mean value of each patch is calculated and subtracted from the corresponding patch. Next, details of the three methods are given.

- The first method: choose fingerprint patches from the training samples at random and arrange these patches as columns of the dictionary matrix.
- The second method: in general, patches from foreground of a fingerprint have an orientation while the patches from the background don't have, as shown in Figure. 2. This fact can be used to construct the dictionary. Divide the interval [00, . . . , 1800] into equal-size intervals. Each interval is represented by an orientation. Choose the same number of patches for each interval and arrange them into the dictionary.
- The third method: it is a training method called K-SVD. The dictionary is obtained by iteratively solving an optimization problem. Y is consisted of the training patches, A is the dictionary, X are the coefficients and Xi is the *i th* column of X. In the sparse solving stage, we compute the coefficients matrix X using MP method, which guarantees that the coefficient vector Xi has no more than T non-zero elements. Then, update each dictionary element based on the singular value decomposition (SVD).

$$\min_{A,X} ||Y - AX||_F^2 \text{ s.t } \forall_i, ||X_i||_0 < T \quad (6)$$

A novel algorithm for adapting dictionaries so as to represent signals sparsely are described below. Given a set of training signals ,the dictionary that leads to the best possible representations for each member in this set with strict sparsity constraints. Here uses the K-SVD algorithm that addresses the above task, generalizing the k-means algorithm. The K-SVD is an iterative method that alternates between sparse coding of the examples based on the current dictionary and an update process for the dictionary atoms so as to better fit the data. The update of the dictionary columns is done jointly with an update of the sparse representation coefficients related to it, resulting in accelerated convergence. The K-SVD algorithm is flexible and can work with any pursuit

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method, thereby tailoring the dictionary to the application in mind.

Compression of the fingerprint

Given a new fingerprint, slice it into square patches which have the same size with the training patches. The size of the patches has a direct impact on the compression efficiency. The algorithm becomes more efficient as the size increases. However, the computation complexity and the size of the dictionary also increase rapidly. The proper size should be chosen. In addition, to make the patches fit the dictionary better, the mean of each patch needs to be calculated and subtracted from the patch. After that, compute the sparse representation for each patch by solving the l_0 problem. Those coefficients whose absolute values are less than a given threshold are treated as zero. For each patch, four kinds of information need to be recorded. They are the mean value, the number about how many atoms to use, the coefficients and their locations. The tests show that many image patches require few coefficients. Consequently, compared with the use of a fixed number of coefficients, the method reduces the coding complexity and improves the compression ratio.

Entropy coding and quantization

Entropy coding of the atom number of each patch, the mean value of each patch, the coefficients and the indexes is carried out by static arithmetic coders. The atom number of each patch is separately coded. The mean value of each patch is also separately coded. The quantization of coefficients is performed using the Lloyd algorithm, learnt off-line from the coefficients which are obtained from the training set by the OMP algorithm over the dictionary.
The first coefficient of each block is quantized with a larger number of bits than other coefficients and entropy-coded using a separate arithmetic coder. The model for the indexes is estimated by using the source statistics obtained off-line from the training set. The first index and other indexes are coded by the same arithmetic encoder. In the following experiments, the first coefficient is quantized with 6 bits and other coefficients are quantized with 4 bits.

Analysis of the algorithm complexity

The algorithm includes two parts, namely, the training process and the compression process. Because the training process is off-line, only the complexity of compression process is analyzed. Suppose the size of the patch is $m \times n$ and the number of patches in the dictionary is N. Each block is coded with L coefficients. L is the average number of non-zero elements in the coefficient vectors. To represent a patch with respect to the dictionary, each iteration of the MP algorithm includes mnN scalar products. The total number of scalar multiplications of each patch is $LmnN$. Given a whole fingerprint image with $M1 \times N1$ pixels. The number of patches of the fingerprint image is approximately equal to $M1 \times N1/m \times n$ Therefore, the total number of scalar multiplications for compressing a fingerprint image is $M1 \times N1/m \times n \times LmnN$, namely, $LM1N1N$.
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.
Fingerprint database for fingerprint compression, which aim both to demonstrate the feasibility of the proposed compression algorithm and to validate the claims of the previous sections. First, the database used in this study is described. Then, the feasibility of the proposed method is proved

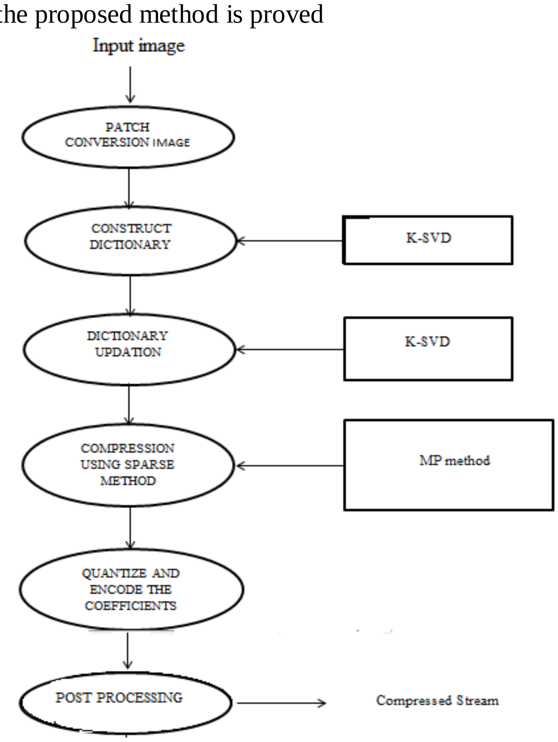

Figure 1. Architecture of fingerprint compression using sparse

CONCLUSION

A new compression algorithm adapted to fingerprint images is introduced. Despite the simplicity of 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 block effect of our fingerprint compression is less serious than that of JPEG. One of the main difficulties in developing compression algorithms for fingerprints resides in the need for preserving the fingerprint image. minutiae which are used in the identification. The algorithm can hold most of the minutiae robustly during the compression and reconstruction.

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