International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 03 Issue: 01 | Jan-2016 www.irjet.net p-ISSN: 2395-0072

A Comparative study of K-SVD and WSQ Algorithms in Fingerprint Compression Techniques

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Abstract - Fingerprint based data security is a most widely used technique in network security. But the size of the fingerprint is the bottleneck in the data transmission. Number of effective algorithms has been used to reduce the size of the fingerprint during data transmission. Here it is considered with two algorithms called K Singular Value Decomposition (K-SVD) and Wavelet Scalar Quantization (WSQ) algorithms. The procedure of both the algorithms is studied and came out with the best one. This survey includes discussion and analysis the two algorithms concepts & description and narrates the best features and many advantages among them.

Key Words: *K Singular Value Decomposition, Wavelet Scalar Quantization algorithms*

1. INTRODUCTION

The problem of image compression is motivated mainly by the great amount of storage used by them. Because of the boom of multimedia applications, and the need for speed in data transmission over the internet, means of reducing the resources needed by images become an important issue. Image compression arise as an answer to the problem caused by the great amount of resoures images can occupy, both in storage space or in bandwidth. Medical, geological, satellite, document, movie images are typical examples of that. The physical or economical limitation of the mentioned resources are compensated by technique like data compression. Compare to all other images like Iris, Palm or face, fingerprints are of great importance in person verification and documentation systems. Such systems are used intensively by both private and government organization where the compression of fingerprint images was approached with different techniques. An implementation of the fingerprint compression standard KSVD was made and its performance compared with WSQ was measured to this particular set of images, by altering its quantization table using a well known bit allocation scheme. The result obtained with such a great number of samples show in a strong way that the KSVD is superior to WSQ for the task of compressing fingerprint images.

Lossy compression technologies usually transform an image into another domain, quantize and encode its coefficients. During the last three decades, transform-based image compression technologies have been extensively researched and some standards have appeared.

The WSQ compression scheme has many advantages such as simplicity, universality and availability. However, it has a bad performance at low bit-rate mainly because of the underlying block-based scheme.

The KSVD-based encoder can be thought of as compression of a stream of 8 × 8 small block of images. This transform has been adopted here. The KSVD based algorithms include three steps: a DWT computation of the normalized image, quantization of the DWT coefficients and lossless coding of the quantized coefficients. The effects on actual fingerprint matching or recognition are also investigated. In most Automatic Fingerprint identification System (AFIS), the main feature used to match two fingerprint images are minutiae (ridges endings and bifurcations).

2. WSQ ALGORITHM

The WSQ class of encoders involves a decomposition of the fingerprint image into a number of sub bands, each of which represents information in a particular frequency band. The sub band decomposition is achieved by a discrete wavelet transformation of the fingerprint image. Each of the sub bands is then quantized using values from a quantization table. The quantized coefficients are then passed to an encoding procedure which compresses the data [3]. The various parts of the compressed image data are identified by special two-byte codes called markers. Some markers are followed by particular sequences of parameters such as table specifications and headers. Others are used without parameters for functions such as marking the start-of-image and end-of-image. When a marker is associated with a particular sequence of parameters, the marker and its parameters comprise a marker segment.

3. K-SVD ALGORITHM

K-SVD is one of the techniques used for fingerprint compression in data transmission. Through this method a new fingerprint compression algorithm based on sparse representation is introduced. 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, it is first constructed with a dictionary for predefined fingerprint image patches. For a new given fingerprint images, represent its patches according to the dictionary by computing minimum size of patches found in the dictionary and then quantize and encode the representation. In this paper, it is considered with the effect of various factors on compression results. The main theme of the algorithm is to construct a base matrix whose columns represent features of the fingerprint images, referring the matrix dictionary whose columns are called atoms; for a given whole fingerprint, divide it into small blocks called patches whose number of pixels are equal to the dimension of the atoms; use the method of sparse representation to obtain the coefficients; then, quantize the coefficients; last, encode the coefficients and other related information using lossless coding methods. In this algorithm, the main feature used to match two fingerprint images are minutiae (ridges, endings and bifurcations). Therefore, the difference of the minutiae between pre and post compression is considered in the project.

This algorithm deals with the eliminating the noise of the image space domain directly. This algorithm has the basic train of thought first determines the template, and then through the analysis in the field of target pixels, pixel gray level to adjust the pixel gray value inside the template and then move the template and repeat the adjustment process until they meet the requirements. An algorithm can be divided into linear denoising algorithm and nonlinear denoising algorithm. Linear denoising cause blindness and serious damage to the detail of image, that is image blur. KSVD algorithm addresses the linear denoising problem which eliminates the noises in the images.

Scholars on the basis of the average algorithm is put forward a lot of improved algorithm, but denoising effect is always not satisfactory. The main idea of this algorithm is based on transformation to get the image on the transform domain, then the image processing and final image is obtained by inverse transformation to achieve the purpose of denoising.

The K SVD algorithm is one of the best method to compress the fingerprint. It uses following steps to compress the fingerprint in an efficient way.

3.1 Construction of the Dictionary

In this work, the dictionary will be constructed in three ways. First, it constructs a training set. Then, the dictionary is obtained from the set. Choose the whole fingerprint images, 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 it is checked 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.

$$S(P_1, P_2) = \min_t \| \frac{P_1}{\|P_1\|_F^2} - t * \frac{P_2}{\|P_2\|_F^2} \|_F^2$$

  where *F* is the Frobenius norm. *P*1 and *P*2 are the corresponding matrices of two patches. *t*, a parameter of the optimization problem, 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. 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 (the middle value of each interval is chosen). 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.

$$\min_{A,X}\{\|Y - AX\|_F^2\} \text{ s.t. } \forall i, \|Xi\|0 < T$$

  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, it is computed the coefficients matrix *X* using MP (Matching Pursuit) method[8], 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).

In the following experiment, the three kinds of dictionaries will be compared.

Compression of a Given 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. 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.

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 [3]. 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 and learnt for the coefficients which are obtained from the training set in 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 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, $LM1N1N$.The Algorithm 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 the 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.

4. COMPARISON STUDY

The wavelet/scalar quantization (WSQ) fingerprint image compression algorithm is effective and has been widely applied to fingerprint image compression. However, WSQ cannot control the compression ratio and its performance on fuzzy images is poor.

Table.1 Resulting compression size of each algorithms.

Actual Size of Fingerprints(kb)	15	18	20	28
WSQ (kb)	9	12	15	19
K-SVD (kb)	6	7	8	11

K-SVD proposed an improved WSQ fingerprint image compression algorithm to overcome the above shortcomings. K-SVD algorithm uses a mixed quantize so that the algorithm can treat fuzzy and non-fuzzy fingerprint images separately. In order to control the compression ratio, an optimization parameters for a specific compression ratio has been used. The proposed algorithm is compared with the traditional WSQ fingerprint image compression algorithm and the results are encouraging.

5. CONCLUSION

On the two algorithms K-SVD and WSQ, the K-SVD algorithm is proved to be good as it includes many features and advantages which is not presents in WSQ algorithm. In K-SVD algorithm, can also works on fixed size square patches, coding each patch separately and adaptively. By this way K-SVD comes with the best result compare to WSQ algorithm

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