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APPLICATION OF SPARSE REPRESENTATION IN FINGERPRINT COMPRESSION

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ABSTRACT: A sparse representation based algorithm is introduced in fingerprint compression. The existing compression system used for Fingerprint Images is not that efficient. As per my literature survey study, there is no method exist so far that use compressive sensing and adaptive learning dictionary to compresses image along with neural network to estimate the results. In the algorithm, we first construct a dictionary for predefined fingerprint image patches. For a new given fingerprint images, represent its patches according to the dictionary and then quantize and encode the representation.

Key words: [lossless compression, Sparse representation, Fingerprint compression.]

1. INTRODUCTION

An important technology in the society is recognising persons by means of biometric characteristics because biometric identifiers can't be shared and they intrinsically represent the individual's bodily identity. Fingerprints are one of many forms of biometrics used to identify individuals and verify their identity. Fingerprint recognition or fingerprint authentication refers to the automated method of verifying a match between two human fingerprints [1]. Large volumes of fingerprint are collected and stored every day in a wide range of applications, including forensic, attendance systematic. In 1995, the size of the FBI fingerprint card archive contained over 200 million items and archive size was increasing at the rate of 30 000 to 50 000 new cards per day [1]. Storage of these fingerprint image databases needs allocation of huge memory space. Fingerprint image compression is a key technique to solve the problem. Compression technologies are classified into lossless and lossy. In the lossless compression exact original images can be reconstructed wherea s in lossy compression an image is transformed into another domain, quantized and encoded. Lossless compression is used where original and reconstructed image should be identical. The two standard options of transformation are the Discrete Wavelet Transformation (DWT) [3] and Discrete Cosine Transformation (DCT) [2] which are used for general image compression. There are special compression algorithms for fingerprint images like Wavelet Scalar Quantization, Contourlet Transform. Fingerprint compression based on sparse representation is introduced here. The algorithm includes construction of the dictionary, compression of a given new fingerprint, quantization and coding and analyzing complexity of the algorithm.

2. RELATED WORKS

The field of sparse representation is relatively young. Early signs of its core ideas appeared in a pioneering work [4]. 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 [5] 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, image denoising, object detection and super-resolution image reconstruction. In paper, 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 neighbour, 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 phenomenonis common in the fields of sparse representation. It doesn't only exist in the face recognition, but also appears in other situations. In paper, [6] 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 [7] [8]. In paper, [7] 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 [8], 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 [9]-[11] for fingerprint image compression under a linear model assumption. In paper [10] [11] the authors showed how to exploit the data dependent nature of Independent Component Analysis (ICA) to compression special images (face and fingerprint images).

The experiments ofthe 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, the authors proposed an algorithm of fingerprint compression based on Nonnegative Matrix Factorization (NMF). 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 nonnegativity. Besides, we think the methods based on sparse representation don't work very well in the general image compression field. The reasons are as follows: the contents of the general images are so rich that there is no proper dictionary under which the given image can be represented sparsely; even if there is one, the size of the dictionary may be too large to be computed effectively. For example, the deformation, rotation, translation and the noise all can make the dictionary become too large. Therefore, sparse representation should be employed in special image compression field in which there are no above shortcomings. The field of fingerprint image compression is one of them. In another paper Fingerprint compression based on sparse representation is done and comparison with the other compression techniques is also explained.

3. METHODOLOGY

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

(A). SPARSE MODELLING

The first element of sparse modelling is dictionary. It will be an N×K matrix, where K is the size of the dictionary. Each column of the dictionary is called as an atom. It's a set of prototype of signals. Instead of one signal we have multiple signals say X i.e. each column is an image patch. One dictionary is used for training all the images and then every one of these images or signals has its own sparse representation. The number of non zero entries of the vector A is very small. Since there are only few non zero entries in vector A, this obtained vector will be sparse and thus called sparse modelling. Given the dictionary, we construct sparse code for every signal.

(B). GREEDY ALGORITHM

The Matching Pursuit [12] is a sparse approximation algorithm which involves finding the best matching projections of the data onto an over complete dictionary D. Matching Pursuit is the greedy algorithm that finds one best atom at a time. The atom that best matches with the signal is selected is kept i.e. why it is called greedy approach Error is checked, if it is below what we wanted, then stop the process. If error is not below the threshold value, then pick another atom which makes the error small. Add that atom to the collection. Again considering the pervious atoms, find the next atom. The algorithm is stopped when the error satisfies the threshold.

(C). QUANTIZATION (Lloyd's Algorithm)

In image processing, quantization is a compression technique achieved by compressing a range values to a single quantum value. Here, Lloyd's algorithm [13] is used for quantization of the sparse matrix. Probability density function of the image is calculated. Then pdf is divided into M intervals. Necessary threshold condition is applied. Apply minimize MSE condition. Again threshold condition and MSE condition are applied until no further decrease in the total MSE is observed. Quantization on the image is applied. Then encoding is performed using arithmetic encoders that encode data by creating a code string which represents a value on the number line between 0 and 1.

CONCLUSION

Fingerprint compression based on sparse representation is introduced here. The algorithm includes construction of the dictionary, compression of a given new fingerprint, quantization and coding and analyzing complexity of the algorithm. This compression technique compare favourably with existing more sophisticated algorithms especially at high compression ratios. However it has higher complexities due to the block by block processing. It can be concluded that sparse representation of fingerprint images provides a better compression ratio compared to other existing compression techniques.

FUTURE SCOPE

There are many areas which can be worked on in future. Different methods for constructing dictionary can be investigated. Samples of different quality of fingerprints can be included. New algorithms for solving the sparse representation and ways reducing the code complexity can be explored. Finally, other applications based on sparse representation for fingerprint images should be explored.

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