Sparse Modeling of Dictionary Learning in Compressive Sensing for Medical Images

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Abstract

Compressive sensing of images encompasses the following stage processes: Representation of sparse signal, constructing the linear measurement and reconstructing of the image. This paper, presents the novelty of representing the sparse signal based on dictionary learning method. The choice of designing the dictionary model based on deep learning methodology, which delivers a simple and expressive structure for designing well-organized and efficient dictionaries. The norm- difference of the image is used of evaluating the performance of dictionary learning based algorithms. Experimental result shows that the Orthogonal matching pursuit (OMP) performance has better output when compared to Least Angle Regression (LAR) algorithm. The result indicates that the sparse modelling using dictionary learning with Orthogonal Matching Pursuit is proficient in CS of MRI images.

Keywords

Compressive sensing, sparse representation, dictionary learning, medical images.

1. Introduction

Compressive sensing (CS) is plays on vital role in signal processing community. The signals can be restored as a compressed form is called the new signal acquisition in a compressive sensing. The signals are basic tools of processing the video clips, medical scans and natural images [1].In sampling theory of CS states that"Images are using significantly fewer measurements than number of unknowns" which is known as Nyquist Sampling. Naturally the image/signal is sparse in original domain or in some transform domain, the acquisition is incoherent, in an appropriate sense, with the transform and to get the better enhancement reconstruction procedure is endured which is nonlinear.CS theory has been applied to MRI images to achieve the high quality reconstructions with lesser measurements. Recently, sparse representation with dictionary learning is applied in MRI images to get the accurate CS recovery. In sparsity based modelling the linear combination of signals are known as atoms,supports in simple and compact models is known us dictionary. Sparsity is the essential prominent tool for dictionary, while modelling the dictionary the one must be cautious about the predictive power of signal classes and efficient compression ability. Earlier the dictionaries were modelled using mathematical functions using harmonic analysis of the signal classes. The analysis of sparse modelling was done using the sparse representation of mathematical dictionaries.

Dictionary Learning (DL) transforms data into sparse representation. The well-known DL method is KSVD [1,2]. It has its role in image denoising [2], compression, sersm data denoising, etc. In image processing, comparing to predefined transformation KSVD reaches high quality accuracy in denoising complicated structures [3, 4]. Since it has high market value it becomes hard to handle practically for

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large scale data. Data-driven tight frame (DDTF)is a recently developed method to gain efficient output. By the term tight frame, we that the frame has a sound reconstruction property i.e., signal representation by means of linear combination of atoms can be specified with products in the signal and dictionary [5,6]. DDTF is used as a catalyst in the property of tight frame of dictionary to enhance the updating step and it takes just one SVD decomposition [6]. Also, it is applied in denoising of data and interpolation of missed trace [6, 7]. For processing signal data of large scale, a rapid version of DDTF is used. A vital is defined to model spare. Originally it was introduced by [8] which help learning through trained data. This sort of representation is called as synthesis sparse modelling. It enables in capturing structures underlying the natural images and it has a good adapting quality for large scale. This process paved wayfor designing algorithms in image processing area such as [10] and to solve inverse problems [9, 10]. In the field of image processing, the application lies exactly in the signals with compact representation. In this chapter, both theoretical and practical approaches are specified to model sparse signal for compressed images.

The objective of this work is to modelling the sparse matrix using dictionary learning method with a help of deep learning architectures for compressive sensing process of medical images. This requires the comparability of the reconstruction algorithms orthogonal matching pursuit (OMP) and least angle regression (LAR).This paper is organized as follows: in Section 2 we give the overview of the dictionary learning. In Section 3 sparse modelling using dictionary learning discussed. Interpretations of the results of the experimentation are shown in section 4 and conclusion is drawn in section 5.

2. Overview of the Dictionary Learning Method

In CS the sparse representation process is the essential for modelling the dictionary. As expected, the signals are sparse and can be restored form the linear projection of space or time measurements [3]. Dictionary can model in the following manner, given signal of small elements x with linear combination of dimension *m*. Here the unit norm functions are atoms and atoms are dictionary. Let us represent D as dictionary and the atoms represent φ_m m = 1, 2……*M*, where *M* represents dictionary size. The dictionary is over complete dictionary when there is span in a signal space with the linearly dependent atoms (M > m).

Dictionary is a signal with the linear combination of atoms,

$$\boldsymbol{x} = \boldsymbol{\varphi b} = \sum_{k=1}^{M} b_k \tag{1}$$

***b* is** not unique when the dictionary is over complete. This is the point where a sparsity constraint has avital role. Decrease of requirements of the sparse, higher the efficiency of sparse representation. With approximation error r for bounded energyγ the sparse linear expansion is obtained. Our main aim is to find sparse vector **b** containing minimal significant coefficients, and the remaining coefficients lesser than are equal to zero. In other words, our objective is to have limited no of resources (atoms) for representing the signal.

The following problem is optimized and formulated as given below:

$$Min||b||_0 \text{ subject to } x = \varphi b + r \quad \text{and } ||r||_2^2 < \gamma \tag{2}$$

Where $||.||_p$represents the l_p norm and the problem is non-deterministic polynomial-time (NP) -hard. In order to obtain the suboptimal solution for vector **b,** the method of approximation algorithms for polynomials with respect to time are used [7]. These approximation algorithms can be divided in to twotypes of classes: the first group uses the pursuit algorithms namely, matching pursuit and the orthogonalMatching pursuit, the basis vectors can selected as iterative optimal vector. The methods of convexrelaxation such as, pursuit denoising and least absolute shrinkage and selection operator, are secondgroup of pursuit algorithms and benefits solves the following problem:

$$Min||x - \varphi b|_2^2 + \lambda \, ||b||_1 \qquad (3)$$

The convex l_1 norm is replaced by non-convex l_0 norm through convex relaxation, where l_0 has nonzero elements and the term norm is used when p approaches zero. Apart from pursuit algorithms other algorithms are also used such as focal underdetermined system solver [10] and sparse Bayesian learning. The evaluation of these techniques on the basis of the quality approximation and the sparsity of the coefficient vector **b** depend signal alone but also depends on the over complete dictionary D. When the techniques are used for particular class of signal **x,** it is understood that not all the dictionariesyield the similar estimation performance [9]. There are several dictionaries that have more similar in leading the sparse solution comparing to others. In these dictionaries the atoms providing the best causesof the target dataset are included. To seek optimized dictionaries is the main target of the methods ofdictionaries.

3. Sparse Modelling Using Over-Complete Dictionaries

In research, three main streams with three algorithm groups are used for dictionary learning. They include 1. probabilistic learning; 2. The learning methods clustering or vector quantization-based learning; 3. particular construction learning with dictionaries. The construction comprises of data structure or focus on managing dictionaries. This section provides three important principles of algorithm representation with three dictionary Learning categories. The over complete dictionary must be well examined than complete dictionary [14]. In order to define over complete dictionaries there, exist two representations namely analysis path and synthesis path. In the area of signal processing, learning is a topic whereas dictionary is referred to represent spare or signal approximation. The dictionary consists of atom collection where atoms refer to real column vectors with length. For example a dictionary with finite number k can be represented as a matrix D with size. Similarly, a sparserepresentation can be represented as a linear combo of dictionary atoms [12].

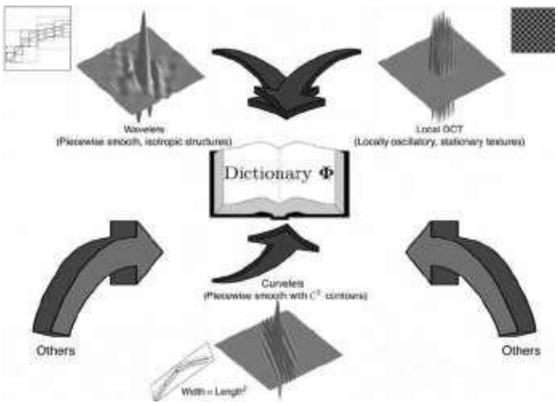

Figure 1: Flow Diagram of dictionary learning

The size of the normal image is too large, it can be partition into N$\times$ N image blocks and sparse modelling can be done using image blocks X = [x_1, x_2, x_3, x_L], each of size $\sqrt{N} \times \sqrt{N}$ pixels, where

$\sqrt{N}$ is an integer value. Learning of dictionaries determines the vector approximation with sparse criteria on coefficients i.e., it allows minimal nonzero coefficients. The dictionary is fit in LHS for the reconstruction to happen on RHS. It is noticed that a better output is retrieved from an undistorted image but here we start with a contradiction [10]. Observing the original image and reconstructed image becomes helped in evaluating the results. If a perfect image is obtained it resembles a Gaussian noise.

Since the real world image is larger we segregate it into smaller blocks and modelling is done in that particular set.

4. Interpretation of results and experimentation

Here it deals with the medical image Cardiac [16] considered for experimentation as shown in Fig.2.Theexecution of software for this method is implemented with the language Python with help of Intel Core (R) 64-bit processor with 8.00 GB RAM, 2.60GHz clock speed on the Windows11operatingsystem. The Dictionary learning domain is applied in sparse Representation using deep learning methodology. Using dictionary model the linear measurement is also achieved to obtain the linear measurement and image reconstruction using the orthogonal matchingpursuit method and least angle regression (LAR) method is executed for the reconstruction of the enhanced image. The CAD cardiac MRI images undergo training with limited time and reconstruction achieved by norm value. The following metrices PSNR, norm value and time are measured to validate the results of CS.

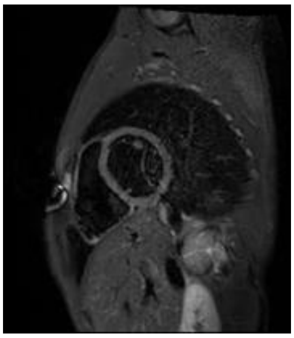

Figure 2: Sample Medical Images

The regional practice of gaining results in denoising image is obtained by comparing the original and reconstructed images. If the reconstructed image becomes perfect then it resembles the Gaussian noise.It can be notified from the plotting that the output from imp with 2 nonzero coefficients is less biased whereas with one non-zero coefficient it becomes a controversy [13].

Table 1: Performance evaluation for Cardiac MRI

Algorithm	Cardiac MRI		
	Time (Sec)	Difference norm	PSNR
OMP (1 atom)	0.4	5.00	33.02 dB
OMP (2 atom)	0.8	4.18	30.01dB
LAR(4 atoms)	5.7	6.18	29.12 dB
Threshold	0.1	6.85	25.01 dB

The Cardiac MRI results of sparse modelling in dictionary learning and reconstructing the image of pursuit algorithm approach is presented in Table 1.

The cardiac MRI images are initially learning from dictionaries and classified into 7076 patches with total training time of (3.0sec.). By training the dataset in deep learning method the cardiac MRI dataset with the single atom dictionary of orthogonal matching pursuit algorithm has obtained the maximum norm value (5.00) with minimum computation time(0.4sec.). Secondly, the dictionary of two atom OMP method is yielded the (4.18) with time consumption (0.8sec.). For the same, sparse dictionary learning and least angle recursion method has shown least performance in terms of norm (6.18), needs more computation time (5.7 sec). Threshold value is obtained the higher norm (6.85) value with minimal time (0.1) but it doesn't provide the desired image. The Measurement metrics PSNR are observed that orthogonal matching pursuit algorithm with single dictionary atom are achieved the desired results (33.02dB) orthogonal matching pursuit algorithm with two dictionary atom performs secondly, threshold performs poor denoising in the PSNR value (25.01 dB). On the whole, Dictionary learning with OMP method is able to accomplish near to the extreme one in terms of all the metrics. It is obvious that, least angle recursion algorithm is the second in performance [11].

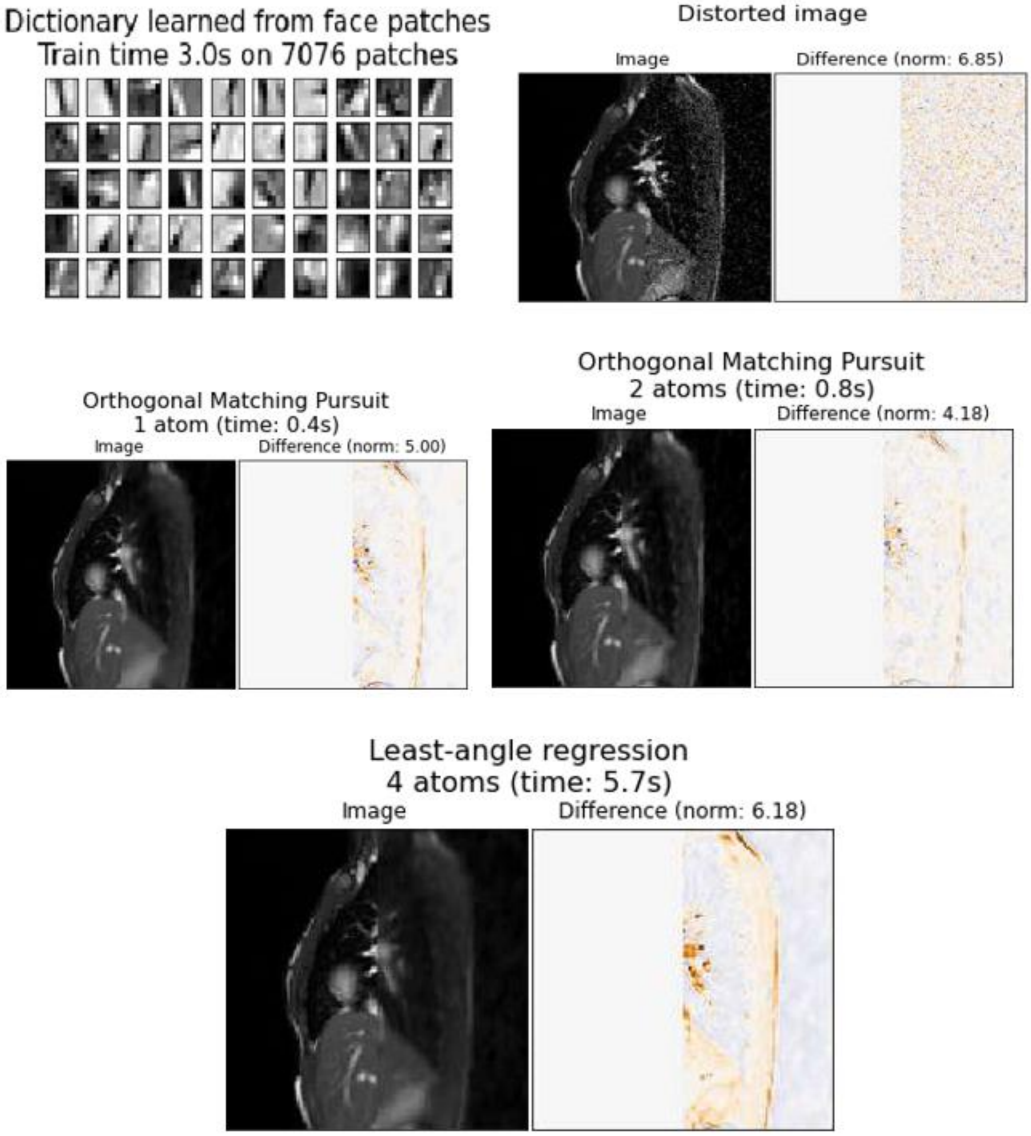

Figure 3: Reconstruction of the images

In addition, it is closer to F norm and LAR is strongly biased with differing intensity value of original image. Though thresholding gives efficient output and is used in other tasks such as object clarificationwith relating visuals, it is less helpful in denoising.

5. Conclusion

In this paper, the novelty of developing the sparse modelling with dictionary learning method using deep learning performs well on MRI images. The performance of the sparse modelling using dictionary learning with least angle regression method and Orthogonal matching pursuit are calculated based on the experimentation using Cardiac MRI image. Generally, to find better output performance the image of reconstructed image or difference norm image and original images are consider.MRI dataset with the single atom dictionary of orthogonal matching pursuit algorithm obtained the highest norm value with minimum time for computation. Sparse dictionary learning and least angle recursion method exhibits low performance concerning norm, which needs more computation time. Threshold value is obtained the higher norm value with minimal time but it doesn't provide the desired image. OM achieves most suitable results compared with performance of LAR. Further work can be done by testing the methods of compressive sensing using the dictionary learning model which can be extended to medical images.

6. References

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