A NOVEL MRI IMAGE RECONSTRUCTION USING COMPRESSED SENSING AND ITS CLASSIFICATION USING SUPPORT VECTOR MACHINE

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Abstract

Magnetic resonance imaging (MRI) is an imaging technique that has played an important role in neuroscience research for studying brain images .X-ray is likewise exceptionally helpful for analyzing the cerebrum and spinal rope related issues. The size of the picture chooses how often the Radio Frequency beat should be applied, subsequently making the MRI examine a tedious procedure. There is a developing prerequisite for decreasing the diagnosing time in MRI requiring examination to quicken this non direct streamlining issue. Compressed Sensing (CS) aims to reconstruct images from considerably smaller measurements than were thought before. Applying CS to MRI offers potentially significant scan time reductions. A technique to MRI remaking from under examined estimations is proposed in this paper. Discrete Wavelet Transform is utilized to meagerly portray MRI. CS remaking is performed utilizing l1 standard by applying Basis pursuit primal- dual interior point method. Trial results uncover that the proposed strategy recreates pictures with great quality. Classification is an important part in retrieval system in order to distinguish between normal patients and those who have the possibility of having abnormalities or tumor. In this paper, we have obtained the feature related to MRI images using discrete wavelet transformation. An advanced kernel based techniques such as Support Vector Machine (SVM) for the classification of volume of MRI data as normal and abnormal will be deployed.

Keyboards— Compressive Sensing, MRI, Primal dual interior point method, Sparse, SVM, Brain Tumor, Classification, Wavelet

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I. INTRODUCTION

Medical Image analysis and processing has great significance in the field of medicine, especially in Non- invasive treatment and clinical study. Medical imaging techniques and analysis tools enable both doctors and radiologists to arrive at a specific diagnosis. Medical Image Processing has emerged as one of the most important tools to identify as well as diagnose various disorders. Imaging helps the Doctors to visualize and analyze the image for understanding of abnormalities in internal structures. The medical images data obtained from Bio-medical Devices which use imaging techniques like Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and mammogram, which indicates the presence or absence of the lesion along with the patient history, is an important factor in the diagnosis [1].

MR image is acquired b y first positioning the patient under a strong magnetic field and then applying the RF pulses along with the application of the Phase Encode Gradient and Frequency Encode Gradient.

An MRI is a costly and time consuming inspection. Long acquisition times are still a difficulty. It limits MRI to use only a few of the many possible contrasts. It also limits

spatial resolution and coverage. Also, high costs are incurred for long acquisition times. It involves limiting the patient in an uncomfortable narrow position and hence reduces patient comfort. If the scan time of MRI is shortened, it might boost patient satisfaction and also reduce medical cost.

For removing aliasing, Nyquist criterion violation exists [3]. In 2004, Emmanuel Candes et al. [4] proved that if the signal‟s sparsity is known, the signal may be reconstructed with fewer samples than the Nyquist theorem insists.

In the previous years, various methods are presented for MRI reconstruction from under sampled measuremets using Block Matching and Adaptive Kernel Methods [5], Graph-based Redundant Wavelet Transform [6], Convolutional neural network [7], deep learning [8], Model-Based Image Reconstruction [9].

Compressive sensing can be combined with Parallel imaging to improve the quality of MRI images. Towards this, the iterative algorithms which are used are more computationally expensive. To overcome this drawback, to speed up reconstruction process the Graphics Processing Units (GPUs) are utilized. These are implemented on massively parallel processors. Various methods are investigated for speeding up CS reconstruction. This includes regularized MRI image reconstruction [10], Cardiac Magnetic Resonance Imaging [11], Barzilai - Borwein and Split Bergman approaches [12] [13] and multiple GPUs [14] and also on 2D cine MRI datasets [15].

In the present work, DCT is used for transformation of the MRI image. Measurement matrix is used for compressive sensing and MRI image is reconstructed by Primal dual Interior point method [16].

The classifications of brain MRI data as normal and abnormal are important to prune the normal patient and to consider only those who have the possibility of having abnormalities or tumor [17].

The shortage of radiologists and the large volume of MRI to be analysed make such readings labor intensive and cost expensive. This calls for an automated system to analyse and classify all the medical images. In dealing with human life, the results of human analysis involving false negative cases must be at very low rate. A double reading of medical imaging could lead to better tumor detection. Recent work [18,19] has shown that classification of human brain in magnetic resonance (MR) images is possible via supervised techniques such as artificial neural networks and support vector machine (SVM) [18] and unsupervised classification techniques such as self-organization map (SOM) [18] and fuzzy c-means[19].

II. MATHEMATICAL FOUNDATION OF COMPRESSIVE SENSING

Let $x \in R^N$ be the signal. An orthonormal basis $\Psi \in R^{NxN}$ sparsifies x if $\theta = \Psi^T$ has only K š N nonzero entries and we can say that x is K-sparse [17]. Ψ compresses x if the entries of θ, when sorted by magnitude will decay according to $|\theta(i)| < Ci^{-1/p}$ for some $p \leq 1$. θ is s – compressible in Ψ if $s = 1/p - 1/2$. By transform coding, the vectors can be compressed and K largest coefficients are retained by magnitude. The remaining coefficients are set to zero.

The Compressive sensing measures inner products of a set of measurement vectors $\{A_1, ...A_M\}$ and the signal. Compressing of the signal is done when M < N. The objective of Compressive sensing is to recover the signal *x* from the smallest possible measurements *y*. Towards this, infinitely many vectors can give the recorded measurements y due to the rank defieciency of matrix $\Upsilon = A\Psi$.

For stable signal recovery, there are conditions on the type and number of measurement vectors. The Restricted Isometry Property (RIP) states the condition to measure the fitness of matrix Υ for CS.

Definition: The K- restricted isometry constant for the matrix Υ, denoted by δ_K, is the smallest nonnegative

number such that, for all $\theta \in R_N$ with $||\theta||_0 = K$.

When the information is measured linearly, reconstruction of signal will become a problem of solving a linear system of equations. Mathematically, the observed data $\mathbf{y} \in C^m$ is related to the signal $\mathbf{x} \in C^N$ through the equation:

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

Since this is a linear measurement process, the vector $x \in CN$ can be recovered by solving the linear system in equation (1).

CS problem consists of reconstruction of a sparse vector

$x \in CN$ from underdetermined measurements

$y = Ax \in Cm, m < N.$ (2)

Hence, CS poses two problems.

- Design of linear measurement matrices i.e,

  determining suitable measurement matrix A.
- Details of efficient reconstruction of x from y.

Matrix A should be designed such that it should cater to all signals x simultaneously. In compressive sensing, the sparsest vector is to be searched in consistent with the measured data. The problem can be stated as l0 minimization.

i.e. Minimize $||\boldsymbol{x}||_0$ subject to Ax = y Unfortunately, solving the l_0 minimization problem can be shown to be NP hard. However, computationally efficient algorithms are well-developed to solve a relaxed version of the problem. Basis pursuit is one of the approaches which can be stated as below.

Minimize $||\boldsymbol{x}||_1$ subject to Ax = y. l_1 norm is a convex function, hence this problem can be solved with efficient techniques from convex optimization.

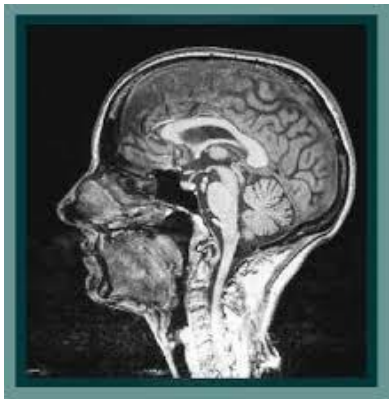
Basis Pursuit is one of the techniques for convex optimization.

III. SPARSITY OF MRI IMAGES

An image can be treated as sparse when its information is defined by only a few pixels, while the contribution of the remaining pixels is near to zero. MR image is a very good example for sparse representation. Still, all the images are not naturally sparse. But by using a transform, these images can be converted to sparse. The images that have only edge information requires a simple transform to achieve good sparse representation.

To demonstrate that the MRI image is sparse, let us consider the following MRI image shown in Fig. 1.

Fig. 1 Sample MRI Image



After the DCT transformation, the DCT coefficients for the MRI image are shown in Table I.

TABLE I

SAMPLE VALUES OF DCT

-0.0000	0.0003	0.0002	0.0029	-0.0000
0.0006	-0.0001	-0.0091	0.0000	0.0006
-0.0002	0.0000	0.0033	0.0022	0.0002
-0.0014	0.0001	0.0082	-0.0001	-0.0002
-0.0000	0.0014	0.0001	0.0034	-0.0000
-0.0009	0.0003	0.0028	0.0019	0.0004
-0.0001	-0.0040	-0.0000	-0.0017	0.0000
-0.0012	-0.0000	0.0009	-0.0000	0.0011
0.0001	-0.0038	-0.0013	0.0001	-0.0014

It can be observed that most of the DCT coefficients are near to zero and the information content is represented by very less values. Thus MRI image provides a good example for sparse representation.

IV. RECONSTRUCTION METHOD

Compressive Sensing consists of mainly three stages.

1. Sparse representation of the image
2. Measurement matrix and
3. Reconstruction algorithm.

The image is transformed from one domain to another domain utilizing one of the Transform to represent the image into sparse domain.

A suitable measurement matrix is designed to reduce the sampled data. Gaussian Random Matrix is used as measurement matrix in this work.

A. *Reconstruction*

To recover the original signal from the measured data, Basis pursuit technique is employed. Optimization challenges can be tackled successfully by the recent advances in interior point methods. Primal dual interior point method has been used for reconstruction of the image.

B. *Basis Pursuit Algorithm*

The recovery of the original image is done by the Image Reconstruction Process. Sparse MR image is reconstructed using the Basis Pursuit algorithm also known as l_1 norm minimization based on Compressive Sensing to achieve an optimal image quality.

The solution is obtained by Primal – dual Interior point method.

The problem to solve in standard form is Minimize $c^T x$

subject to $Ax = y$ $x \geq 0$;

where c, $x \in R^n$, $y \in R^m$ and A is an $m \times n$ matrix. This is called the primal problem.

The dual problem can be represented as Maximize $b^T y$ subject to $A^T y \leq c$

Newton equations for the logarithmic barrier representation of problem is defined by

$$\begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ S & 0 & X \end{bmatrix} \begin{bmatrix} \delta x \\ \delta y \\ \delta s \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ -XSe + \tau\gamma e \end{bmatrix}. \quad (3)$$

where r∈ [0, 1] is a is a duality measure [16].

C. *Inverse Transform*

The final stage is the Inverse Transform. The inverse of the DCT reconstructs a sequence from its discrete cosine transform coefficients. Image is reconstructed using the Inverse Discrete Cosine Transform (IDCT).

V. CLASSIFICATION USING SUPPORT VECTOR MACHINE (SVM)

The aim of classification is to group items that have similar feature values into groups. Classifier achieves this by making a classification decision based on the value of the linear combination of the features. SVM is a binary classification method that takes as input labelled data from two classes and outputs a model file for classifying new unlabeled/labelled data into one of two classes. The SVM originated from the idea of the structural risk minimization that was developed by Vapnik [20].

Support vector machines are primarily two class classifiers that have been shown to be attractive and more systematic to learning linear or non-linear class boundaries. The use of SVM, like any other machine learning technique, involves two basic steps namely training and testing. Training an SVM involves feeding known data to the SVM along with previously known decision values, thus forming a finite training set. It is from the training set that an SVM gets its intelligence to classify unknown data. In SVM, for two class classification problem, input data is mapped into higher dimensional space using RBF kernel. Then a hyper plane linear classifier is applied in this transformed space utilizing those patterns vectors that are closest to the decision boundary [7]. Let *m*-dimensional inputs x*i* (*i*

= 1, . . .,*M*) belong to Class 1 or 2 and the associated labels be *yi*= 1 for Class I and −1 for Class II. Decision function for SVM is $D(x) = w\ t\ x + b$

where w is an *m*-dimensional vector, *b* is a scalar, and yi D(xi)≥1 for i=1, . . .,M.

The distance between the separating hyper plane $D(x) = 0$ and the training datum nearest to the hyper plane is called the margin. The hyper plane $D(x) = 0$ with the maximum margin is called the optimal separating hyper plane.

VI. EXPERIMENTAL RESULTS

This section gives the results of the proposed method. The images are cropped to a size of 100×100 pixels. Thus, the total amount of information is 10000 pixels, on which we take 3000, 4000, 5000, 6000 and 7000 measurements respectively. The reconstructions are conducted on I7 personal computer. Each iteration of the compressive sensing takes about 18 seconds and the process converges in about 20 iterations. Thus the entire reconstruction process takes about 6 minutes.

Comparison with different measurement values "*m*" are as depicted in Fig. 2.

PSNR values for these measurements are tabulated in Table II.

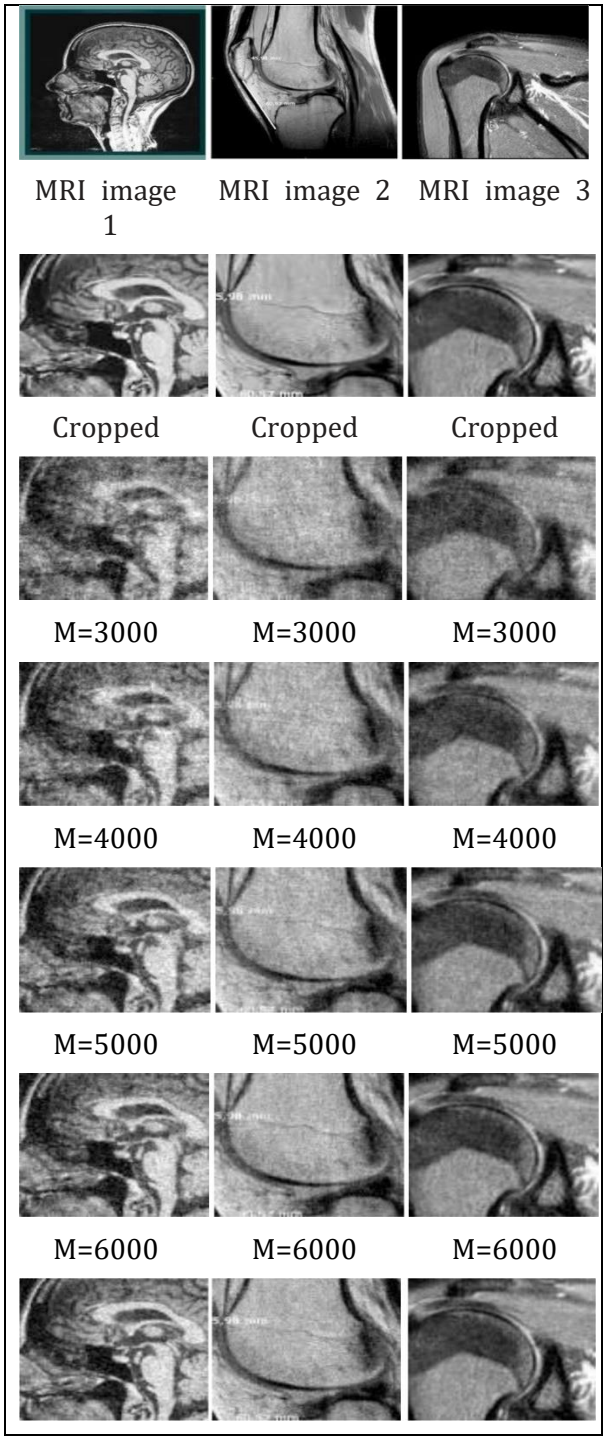
Results shows that the compressive sensing reconstruction has much better visual quality, which are not visible in the traditional reconstruction.

TABLE II PSNR VALUES FOR DIFFERENT MEASUREMENT (M) VALUES

Image	m=3000	m=4000	m=5000	m=6000	m=7000
Image 1	18.36	19.75	21.5	23.02	25.5
Image 2	21.0	22.01	23.7	25.23	27.3
Image 2	21,73	23.64	25.95	28.03	30.6

VII. RESULTS AND DISCUSSION

Feature extraction has been implemented using Matlab 7.9. Each of the images produces 17689 wavelet approximate coefficients. The main advantage of wavelets is that they provide localized frequency information about a function of a signal, which is particularly beneficial for classification. By using the wavelets, a given function can be analyzed at various levels of resolution. The algorithm described in this project is developed locally using a combination of the Image Processing Toolbox and Wavelet toolbox (The MathWorks) for MATLAB. The matrix of coefficient is 133 x 133 double.



In every wavelet–coded MR image, a classifier has been applied to determine whether it is normal or abnormal. The parameter of '0' is for abnormal whereas '1' is for normal image. The result from feature extraction will be used as input for classification.

A. Classification Using Support Vector Machine (SVM)

The type of SVM which has been used is 'c_svc' which means multiclasses. The parameter for kernel type is using Radiant Basis Function (RBF). The settings of 'kernel type', 'gamma' and 'rho' are done by default of the software. Also, we are using class 2 which actually means 'normal' and 'abnormal'. The labels for these classes are using '1' and '0' for 'normal' and 'abnormal' respectively. The numbers of normal images which counted for training set is 20 whereas for abnormal images is eleven. By accomplishing the training set, we can therefore use it into learning algorithm.

The learning algorithm then outputs a function, which for historical reasons is called the hypothesis. The hypothesis' job is to take a new input and give out an estimate output or class. The parameters that define the hypothesis are actually things that 'learned' by the training set.

Several testing have been done with some Brain MRI images. From the testing, all normal have been classified successfully but not for abnormal ones. Due to this misclassified the classification results with RBF kernel has got an accuracy of 65% where only 39 images are successfully classified from 60 Brain MRI whereas 21 images are not.

The algorithm that has been developed probably cannot work on sets of sample points that are too large, for two reasons:

- Limited data precision
- Computational complexity (time, and also space)

However, large sets of training points (thousands per tissue class) are needed by the final supervised non-parametric classifier in order to perform well.

VIII. CONCLUSION

The paper presents an algorithm for MRI image reconstruction, from under sampled data. DCT is used for sparsifying this data and basis pursuit is employed for image reconstruction experiments. Experimental results reveal that reconstructed images are of good quality. PSNR values quantify the efficacy of proposed technique. This work also involves using SVM to classify the input which is MRI Brain into normal and abnormal classification. We intend to prove that this kennel technique will help to get more accurate result. SVM actually cannot work accurately for a large data due to the training complexity of SVM itself which is highly dependent on the size of data [21]. For future work, we will try to use 1/3 or ½ of the data for testing and will hope to see the performance improve on accuracy.

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