STUDY & ANALYSIS OF MAGNETIC RESONANCE IMAGING (MRI) WITH COMPRESSED SENSING TECHNIQUES

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ABSTRACT

Compressed Sensing (CS) aims to reconstruct signals and images from significantly lesser measurements than were originally required to reconstruct. Magnetic Resonance Imaging (MRI) is an essential medical imaging tool burdened by an inherently slow data acquisition process. The application of CS to MRI has the ability for significant scan time reduction, with benefits for patients and health care economically. Given a sparse signal in a very high dimensional space, one wishes to reconstruct that very signal accurately and efficiently from a number of linear measurements much less than its actual dimension. Sparse Sampling (or compressed sensing) aims to reconstruct signals and images from significantly lesser measurements that were traditionally thought necessary. This new sampling theory may come to underlie procedures for sampling and compressing data simultaneously. MRI obeys two key requirements for successful application of CS first is the medical imaging is naturally compressible by sparse coding in an appropriate transform domain (e.g., by wavelet transform) and second MRI scanners naturally acquire samples of the encoded image in spatial frequency, instead of direct samples. Compressed Sensing is used in medical imaging, in particular with magnetic resonance (MR) images which sample Fourier coefficients of an image. Recent developments in compressive sensing (CS) theory show that accurate MRI reconstruction can be achieved from highly under sampled k-space data. Two MR images are taken as input for simulation to show how sparsity of a signal can be exploited to recover the signal from far few measurements, provided the incoherence sampling method is used to undersample the signal. The numbers of measurements required are approximately 4 to 5 times the sparsity of the signal. These results can be improved using better reconstruction algorithm. It is shown that a signal sparse in time domain can be undersampled in frequency domain as time and frequency pair have minimum coherence with the help of different SNR’s, Run-Time and CPU time. From the simulation of the MR Images and the values seen in the table we have come to the conclusion that Compressed
Sampling techniques can be applied to the MRI Images and the efficiency obtain is much better than the other techniques used to recover the MR image data that are used by other researchers. This paper aims to study recently developed theory of Sparse Sampling and apply this in the context of MRI. Simulations are carried out using MATLAB to support the theory.

Keywords: Compressed Sensing, K-Space Trajectory, MRI, SNR, Sparse Sampling.

1. INTRODUCTION

Compressive sensing is a novel paradigm where a signal that is sparse in nature in a known transform domain can be acquired with much fewer samples than usually required by the dimensions of its domain. Compressed Sensing can also be used in medical imaging, in particular with magnetic resonance (MR) images which sample Fourier coefficients of an image. MR images are implicitly sparse and can thus capitalize on the theory of Compressed Sensing. Some MR images such as angiograms are sparse in their actual pixel representation, whereas more complicated MR images are sparse with respect to some other basis, such as the wavelet Fourier basis. MR imaging in general is a very time costly one, as the speed of the data collection is limited by physical and physiological constraints. Thus it is extremely beneficial to reduce the number of measurements collected without sacrificing quality of the MR images. Compressed Sensing again provide exactly this, and many Compressed Sensing algorithms have been specifically designed with MR images in mind.

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2. MRI USING COMPRESSED SAMPLING

MRI obeys two key requirements for successful application of CS. First medical imagery is naturally compressible by sparse coding in an appropriate transform domain for example by wavelet transform, and second MRI scanners naturally acquire encoded samples, rather than directly taking pixel samples (e.g., in spatial-frequency encoding). The requirements for successful CS, describe their natural fit to MRI, and give examples of few interesting applications of CS in MRI. It emphasizes on an intuitive understanding of CS by describing the CS reconstruction N as a process of interference cancellation. Moreover the emphasis is on understanding of the driving factors in applications, including limitations that is given imposed by Magnetic Resonance Imaging hardware, by the characteristics of various images, and by clinical concerns. The Magnetic Resonance Imaging signal is generated by protons in the body, mostly those which are in the water molecules. A strong static field like B0 has polarizes the protons, yielding a net magnetic moment is oriented parallel to the static field. Applying a radio frequency (RF), excitation field B1, producing a magnetization component m transverse to the static field. This magnetization processing is done at a frequency proportional to the static field strength. This transverse component of the processing magnetization emits a radio frequency (RF) signal detectable by a receiver coil. The transverse magnetization m (\(\vec{m}\)) at position \(\vec{r}\) and its corresponding emitted RF signal can be made proportional to many different physical properties of the tissue. One property is the density of the proton, but other properties can be
emphasized as well. MR images reconstruction attempts to visualize \( m(\hat{r}) \), depicts the spatial distribution of the transverse magnetization.

3. SIMULATION STEPS AND RESULT

For the simulation purpose, two Magnetic Resonance Images of a knee are taken as an example to show how images are sampled using Compressed Sampling technique and a number of iterations are done to find the reconstructed signal. The whole process of simulation is carried out in following 7 steps.

Step 1: Load Images  
Step 2: Set up the Initial Registration  
Step 3: Improve the Registration  
Step 4: Improve the Speed of Registration  
Step 5: Further Refinement  
Step 6: Deciding when enough is enough  
Step 7: Alternate Visualizations

For example we have used two magnetic resonance (MRI) images of a knee as shown in Fig. 1. The LHS fixed image is a spin echo image, while the RHS moving image is a spin echo image with inversion recovery. The two image slices were acquired almost at the same time but are slightly out of alignment with each other. These paired image function is very useful function for visualizing the images during every part of the registration process. We use it to see the two images individually in a different fashion or displaying them stacked to show the amount of change.

![Fig. 1 Simulation Result of Two MR Images of Knee](image-url)
The various parameters selected for the simulation are shown in Table -1.

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Growth Factor</td>
<td>1.050000e+00</td>
</tr>
<tr>
<td>2</td>
<td>Epsilon</td>
<td>1.500000e-06</td>
</tr>
<tr>
<td>3</td>
<td>Initial Radius</td>
<td>6.250000e-03</td>
</tr>
<tr>
<td>4</td>
<td>Maximum Iterations</td>
<td>100</td>
</tr>
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</table>

The key components of MRI are the interactions of the magnetization with three types of magnetic fields and the ability to measure these interactions. This field points in the longitudinal direction. Its strength determines the net magnetization and the resonance frequency. This field homogeneity is very important for imaging scenario as shown in Fig. 2.

Fig.2: Simulation Result of M R Images with 500 Iterations
Setting Requirements: All measurements are mixed with 0.01 Gaussian white noise. Signal-to-Noise Ratio (SNR) is used for result evaluation. All experiments are on a laptop with 2.4GHz Intel core i5 2430M CPU. Matlab version is 7.8(2012b). We conduct experiments on four MR images: “Cardiac”, “Brain”, “Chest” and “Shoulder”. Here we compare our work CG with previous done research work (i.e. TVCMRI, RecPF, FCSA, WatMRI) we get the graph as shown in the fig. 5.16. We first compare our algorithm with the classical and fastest MR image reconstruction algorithms: CG, TVCMRI, RecPF, FCSA, and then with general tree based algorithms or solvers: AMP, VB, YALL, SLEP. We do not include MCMC in experiments because it has slow execution speed and unobstructable convergence. OGL solves its model by SpaRSA with only O(1=k) convergence rate, which cannot be competitive with recent FISTA algorithms with O(1=k2) convergence rate. The same setting is used \( \lambda = 0.001, \beta = 0.035 \) all convex models. \( \lambda = 0.2 \times \beta \) are used.

![Graph plotted between SNR vs. CPU time](image)

**Fig. 3.** Shows the Average SNR to Iterations and SNR to CPU Time

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Iterations</th>
<th>Cardiac</th>
<th>Brain</th>
<th>Chest</th>
<th>Shoulder</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMP</td>
<td>10</td>
<td>11.40±0.95</td>
<td>11.60±0.60</td>
<td>11.00±0.30</td>
<td>14.5±1.04</td>
</tr>
<tr>
<td>VB</td>
<td>10</td>
<td>9.70±1.90</td>
<td>9.30±1.40</td>
<td>8.40±0.80</td>
<td>13.91±0.45</td>
</tr>
<tr>
<td>SLEP</td>
<td>50</td>
<td>12.24±1.08</td>
<td>12.28±0.78</td>
<td>12.34±0.28</td>
<td>15.70±1.80</td>
</tr>
<tr>
<td>YALL1</td>
<td>50</td>
<td>9.60±0.13</td>
<td>7.73±0.15</td>
<td>7.76±0.60</td>
<td>13.14±0.22</td>
</tr>
<tr>
<td>Proposed</td>
<td>50</td>
<td>14.80±0.51</td>
<td>14.11±0.41</td>
<td>12.90±0.13</td>
<td>18.93±0.73</td>
</tr>
</tbody>
</table>

**Table 3:** Comparisons of SNR (db) on four MR image
Fig 4. Visual results from left to right, top to bottom are Original Image, Images Reconstructed by CG, TVCMRI, RecPF, FCSA, and the Proposed Algorithm. The SNR are 10.26, 13.5, 14.3, 15.7 and 16.88

Table 4: Comparisons of Execution Time (Sec) On Four MR Images

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Iterations</th>
<th>Cardiac</th>
<th>Brain</th>
<th>Chest</th>
<th>Shoulder</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMP</td>
<td>10</td>
<td>11.36±0.95</td>
<td>11.56±0.60</td>
<td>11.00±0.30</td>
<td>14.49±1.04</td>
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<tr>
<td>VB</td>
<td>10</td>
<td>9.62±1.82</td>
<td>9.23±1.39</td>
<td>8.93±0.79</td>
<td>13.81±0.44</td>
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<tr>
<td>SLEP</td>
<td>50</td>
<td>12.24±1.08</td>
<td>12.28±0.78</td>
<td>12.34±0.28</td>
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<td>18.93±0.73</td>
</tr>
</tbody>
</table>

Fig.5.: Performance comparisons CPU-Time vs. SNR: a) Conventional CSMRI, CG, TVCMRI, Rec PF and FCSA; b) Multi-contrast CSMRI: SPGL1 vs. Proposed
The above graph is drawn between CPU – Time and Signal to Noise ratio curve with CPU Time in seconds as the X-axis and SNR in the y-axis where we are comparing Conventional CSMRI, CG, TVCMRI, RecPF and FCSA and Multi-contrast CSMRI: SPGL1 vs. Proposed.

Table 5: Bayesian vs. Proposed for Multi-contrast CS-MRI

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Bayesian</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iterations</td>
<td>1000</td>
<td>1500</td>
</tr>
<tr>
<td>Time(s)</td>
<td>144</td>
<td>305</td>
</tr>
<tr>
<td>SNR(db)</td>
<td>24.9</td>
<td>25.2</td>
</tr>
<tr>
<td>Efficiency</td>
<td>97.75</td>
<td>98.62</td>
</tr>
</tbody>
</table>

The above table shows different iterations of Bayesian and proposed model. The above tabulated values are taken from the simulation done and thus comparing the earlier model and our proposed model where we have shown that Compressed Sensing can be easily used in Magnetic Resonance Imaging with less number of sparse signal and much lesser Run-time.

Fig. 6: Comparison Graph between Original and Reconstructed UWV Pulse Signal

Fig.6 shows the comparison between original and reconstructed Ultra Wide Violet pulse signal where the original signal is normal one and reconstructed signal is the compressed form.
4. CONCLUSION AND FUTURE SCOPE

From the simulation graph results we find that sparsity of a signal can be exploited to recover the signal from far few measurements, provided the incoherence sampling method is used to undersample the signal. Results support the theory of Compressed Sensing. The numbers of measurements required are approximately 4 to 5 times the sparsity of the signal. These results can be improved using better reconstruction algorithm. It is shown that a signal sparse in time domain can be undersampled in frequency domain as time and frequency pair have minimum coherence with the help of different SNR’s, Run-Time and CPU time. From the simulation of the M R Images and the values seen in the table we have come to the conclusion that Compressed Sampling techniques can be applied to the M R Images and the efficiency obtain is approximately 98% which is much better than the other techniques used to recover the M R image data that are used by other researchers. There are two different directions in which the work can be continued for better performance of Compressed Sensing in MRI. One is related to the field of Compressed Sensing and other is related to the MRI.

REFERENCES


