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Embedded Magnetic Resonance Image Reconstruction Using Compressed Sensing

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Abstract— **The availability of embedded processing platform has made it possible for many applications to utilize such platforms to go down in size and cost while maintaining the performance. In this work, we investigate the use of an embedded platform based on the OMAP processor for a challenging image reconstruction in magnetic resonance imaging. An algorithm based on the compressed sensing theory was implemented on the embedded platform and the performance was measured and compared to other platforms. This work shows interesting preliminary results and points to several future directions for performance optimization in utilizing such embedded platforms in practical medical imaging applications.**

Keywords— **Magnetic Resonance Imaging, Image Reconstruction, Compressed Sensing, BeagleBoard, OMAP, DSP.**

I. Introduction

Time is a very important factor in medical imaging, there will always be a tradeoff between imaging time and image quality which is also a very important factor. Imaging speed is limited by many constraints like physical factors (e.g. slew rate in MR), physiological factors and processing speed [6].

Any imaging system contains two main stages the first is data collection and the second is image reconstruction, in MRI the time needed for the first stage is related to the amount of data collected which according to Nyquist criterion depends on the resolution of the image and field of view and not following this criterion causes image artifacts in linear reconstructions [1],[8], also time needed for image reconstruction depends on the processing power of the machine and complexity of the reconstruction algorithm and of course the size of data.

Compressed sensing (CS) Theory tries to reduce the measurements needed to reconstruct the image without significantly degrade the image quality [3]-[5], and to make this possible CS depends on two factors *sparsity* and *incoherence* [2]. Sparsity implies that the underlying object has a sparse representation (compressible) in a known domain and this is made in image compression (Transform Based Compression) in JPEG, JPEG-2000, and MPEG standards [9]. Incoherence is that the artifacts caused in linear reconstruction due to reduction in data collected should be noise like in the sparsifying domain [6].

In order to apply CS on MRI we need the two previous conditions to be found in MR images, first for sparsity we will find that most MR images are sparse in a certain transform domain. Angiograms are sparse in the pixel representation and look sparser by spatial finite-differencing, brain images are sparse in certain domains like wavelet domain. Second a specific sampling criterion such as taking a completely random set of the k-space is used to achieve incoherent sampling for MRI [1]. In MRI the data collected are simply individual Fourier coefficients (k-space). In CS, we only need to acquire a subset S of k-space coefficients and the reconstruction is obtained through solution of an optimization problem [1].

In this paper we compare straightforward implementations of the compressed sensing reconstruction algorithm on different processing platforms including embedded processors to verify the performance of such platforms.

II. Methodology

The image is reconstructed using CS through solving the following optimization problem:

$$\begin{aligned} &minimize && \|\psi m\|_1 \\ &subject\ to && \|F_S m - y\|_2 < \epsilon, \end{aligned} \quad (1)$$

While F_S denotes the Fourier transform evaluated just at frequencies in subset S, ψ is the sparse transform, m is the reconstructed image, y is the measured k-space data from the MR scanner and ϵ controls the fidelity of the reconstructed data [1],[2].

Minimizing the l_1- norm of ψm promotes sparsity (when minimizing l_1-norm, the reconstruction is exact but if using l_2-norm it does not give reasonable approximation for the original signal) [3]-[5]. The constraint $\|F_S m - y\|_2 < \epsilon$ enforces data consistency [1]. Many methods are used to solve the optimization problem (1) and include projections onto convex sets [10], iterative soft thresholding [11]-[13] and iteratively weighted least squares [14]-[15]. Here, we utilize the nonlinear conjugate gradient with fast and cheap backtracking line-search similar to [6],[16]-[18]. Algorithm is illustrated in Fig. 2.

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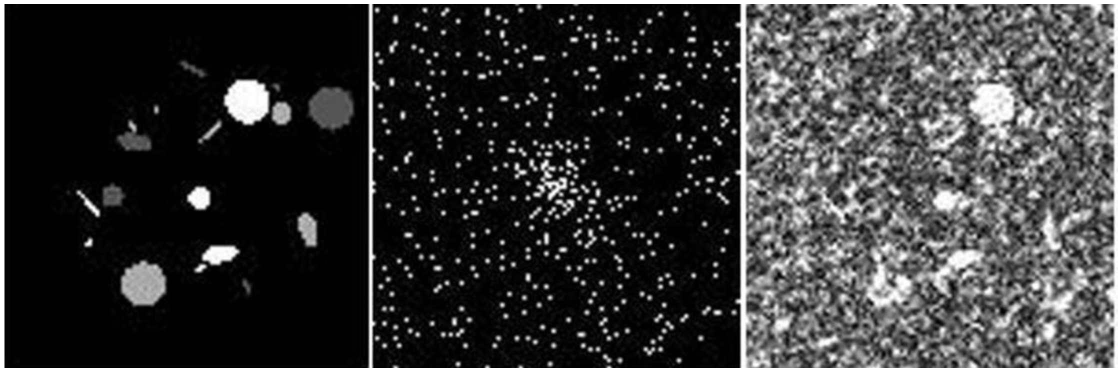


(a) (b) (c)

Fig. 1. (a) Original image. (b) Sampling pattern. (c) ZF-w/dc.

To test different platforms, an angiography-like simulated image with a size of 100×100 pixels and containing randomly generated vessels with different sizes and magnitudes as shown in Fig. 1(a). The k-space of the image was undersampled with a factor of 20 with a randomly generated sampling pattern shown in Fig. 1(b), and as an initial guess for the algorithm we used a zero filling with density compensation (ZF-w/dc) reconstructed image Fig. 1(c). ZF-w/dc is the reconstruction by zero-filling the missing k-space data and k-space density compensation [6]. The quality of the resultant image is compared to the original image and, a low-resolution reconstruction (obtained by the reconstruction of centric ordered data with the same number of data points as the undersampled set used in CS reconstruction) using mean-squared error (MSE) and signal-to-noise ratio (SNR) [7].

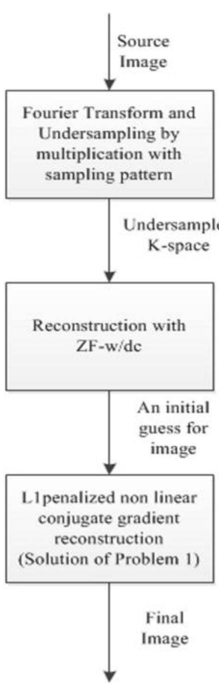


Fig.2. Algorithm block diagram

We implemented the algorithm that solves problem (1) using the standard *C* language and *gcc* 4.6.3 (Free Software Foundation, Inc., Boston, USA) on *Ubuntu* 11.10 (Canonical Ltd., London, United Kingdom) using a platform containing an Intel® Core™ Duo Processor *T2450* 2.00 GHz (Intel Corporation, USA). The memory used by the program was optimized and reduced in order to be suitable for the limited memory on some of the platforms used for test.

We tested the algorithm on three different platforms; the first contains the previously mentioned Intel® Core™ Duo Processor, the second contains Intel® Core™ *i7-2630QM* CPU 2.00GHz (Intel Corporation, USA) using *gcc* 4.6.3 on *Ubuntu* 11.10, the third was a BeagleBoard containing *OMAP3530* (Texas Instruments Inc., Texas, USA) application processor which contains a microprocessor unit (MPU) subsystem based on a 720 MHz *ARM* Cortex™-A8 microprocessor and an IVA2.2 subsystem with a *C64x+* digital signal processor (DSP) core, and the algorithm was tested on the *ARM* using *EGLIBC* 2.16 (Linux Foundation, USA) and on the *DSP*.

In order to run the OMAP we need first to load it with an

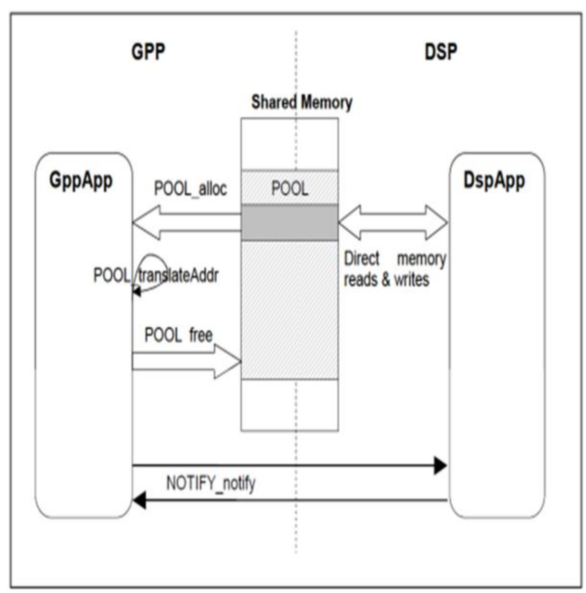
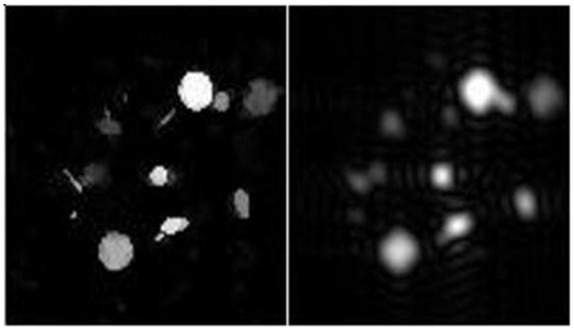


Fig. 3.Communication with DSP.

embedded operating system (Windows based or Linux based), we build Ångström system which is a complete Linux distribution and includes the kernel, a base file system, basic tools and a package manager to install software from a repository. It uses the Open Embedded (OE) platform, a tool-chain that makes cross-compiling and deploying packages easy for embedded platforms, also an inter-processor communication system (DSP/BIOS Link) Fig.3, was built between the two processors (ARM and DSP) to allow passing messages and data for testing algorithm from the ARM (that works as a general purpose processor GPP) side to the DSP side to perform it.



(a) (b)

Fig. 4. (a) CS resulting image. (b) Low resolution image.

III. Results and discussion

After testing the algorithm on the core duo processor we get the reconstructed image using CS as shown in Fig. 4(a) and the low resolution reconstruction as in Fig. 4(b), if we compared the resulting images with the original image we see that the degradation in image quality for the image by CS is small and most of image details are reserved, but for the image by low resolution reconstruction we find that the image is very blurred. According to the data in TABLE I we see that the CS reconstructed image is better than the low resolution reconstructed image in both MSE and SNR.

The performance of the algorithm after trying it on the different platforms is shown Table II. All the processors give longer processing time than the time expected for this algorithm especially on the DSP while that on the ARM processor was found to be surprisingly close to significantly larger processing platforms. This is apparently due to the dependence of the algorithm on 2D Fourier transform and the prolonged loops which take long processing time. The excessive processing time obtained when running the same algorithm on the DSP was difficult to explain at first until further research was done and that revealed the different architecture of this platform that requires very different coding strategy to take advantage of the available computing hardware on the processor. Hence, simple porting of code running on other general purpose processors is not a good strategy to develop efficient code on DSPs.

Difficulties were also found in attempting to transfer data between the ARM and DSP parts of the OMAP processor. The amount allowed using the data passing interface allowed limited data packets that barely allowed the 100×100 sized image to be transferred for processing. This is clearly a very challenging problem facing the porting of such algorithms into embedded DSPs.

TABLE I
Comparison between CS and Low Resolution resulting images

Image	MSE	SNR
CS	0.0021	9.9142
Low Resolution	0.0075	2.6107

TABLE II
Time performance of the algorithm on each processor

Image	Processing Time (min)
Core duo	22.5
Core i7	16.5
ARM	30.1
DSP	About 1000

It should be noted that the algorithm used was implemented using serial code. This did not clearly take advantage of the number of processors available on the processing platform used. Hence, the difference between the first two Intel-based platforms with 2 and 8 processors can be attributed only to differences in clock speed rather than number of processor.

IV. Conclusion

The results indicate confirmed the theory of compressed sensing as a powerful method of image reconstruction under very low sampling conditions. The processing time of the algorithm is compared on different processing platforms with results indicating interesting performance for the embedded ARM processor part of the OMAP processor. Also, the results indicated that the porting of such sophisticated algorithm to the DSP was not straightforward and that simple porting resulted in a very poor performance. So, special coding methods that take advantage of the architecture of the DSP to utilize the vectored computational hardware and pipelining must be carefully mapped onto the algorithm before it is ported. Further investigation is needed to develop specific porting instructions to allow the performance of the DSP to reach its theoretical limit.

References

[1] M. Lustig, D.L. Donoho, J.M. Santos, and J.M. Pauly, "compressed sensing MRI," *Sig Proc Mag*, vol. 25 , no. 2, pp. 72-82, 2008.

[2] E.J. Candès and M.B. Wakin, "An Introduction To Compressive Sampling," *IEEE Sig Proc Mag*, vol. 25, no. 2, pp. 21-30, 2008.

[3] E. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information," *IEEE Trans. Inform. Theory*, vol. 52, no. 2, pp. 489–509, 2006.

[4] D. Donoho, "Compressed sensing," *IEEE Trans. Inform. Theory*, vol. 52, no. 4, pp. 1289-1306, 2006.

[5] E. Candès and T. Tao, "Near optimal signal recovery from random projections: Universal encoding strategies?," *IEEE Trans. Inform. Theory*, vol. 52, no. 12, pp. 5406–5425, 2006.

[6] M. Lustig, D.L. Donoho, and J.M. Pauly, "Sparse MRI: The application of compressed sensing for rapid MR imaging," *Magn. Reson. Med*., vol. 58, no. 6, pp. 1182–1195, 2007.

[7] Y. Zhang, H.D. Cheng, J. Huang, X. Tang, "An effective and objective criterion for evaluating the performance of denoising filters," *Pattern Recognition*, vol. 45, pp. 2743–2757, 2012.

[8] G. Wright, "Magnetic resonance imaging," *IEEE Signal Processing Mag.*, vol.14, no. 1, pp. 56–66, Jan. 1997.

[9] D.S. Taubman and M.W. Marcellin, JPEG 2000: Image Compression Fundamentals, Standards and Practice *(The Springer International Series in Engineering and Computer Science),* Norwell, MA: Kluwer, vol. 642, 2002.

[10] E. Candès, J. Romberg "Signal recovery from random projections." *In: Proc. SPIE Conf. Comput. Imaging III,* Mar. 2005, vol. 5914, pp. 76-86.

[11] I. Daubechies, M. Defrise, C. De Mol. "An iterative thresholding algorithm for linear inverse problems with a sparsity constraint." *Comm. Pure Applied Mathematics*, vol. 57, no. 11 pp. 1413 – 1457, 2004.

[12] J. Starck, M. Elad, D. Donoho "Image decomposition via the combination of sparse representation and a variational approach." *IEEE Trans. Image Proc.*, vol. 14, no. 14, pp. 1570–1582, 2005.

[13] M. Elad, B. Matalon, M. Zibulevsky "Coordinate and subspace optimization methods for linear least squares with non-quadratic regularization". *Journal on Applied and Computational Harmonic Analysis*, vol. 23, no. 3, pp. 285-418, 2007.

[14] J. Ye, S. Tak, Y. Han, H. Park. "Projection reconstruction MR imaging using FOCUSS".*Magn. Reson. Med.*, vol. 57, no. 4, pp. 764–775, 2007.

[15] D. Donoho, M. Elad, V. Temlyakov. "Stable recovery of sparse overcomplete representations in the presence of noise". *IEEE Trans. Info. Thry*; vol. 52, no. 1, pp. 6–18, 2006.

[16] T. Chang, L. He, T. Fang. "MR image reconstruction from sparse radial samples using bregman iteration". In: *Proc. of the 13th Annual Meeting of ISMRM, Seattle*, 2006, pp. 696.

[17] K. T. Block, M. Uecker, J. Frahm. "Undersampled radial MRI with multiple coils. Iterative image reconstruction using a total variation constraint".*Magn. Reson. Med.* 2007; vol. 57, no. 6, pp. 1086–1098, 2007.

[18] M. Bronstein, A. Bronstein, M. Zibulevsky, H. Azhari. "Reconstruction in diffraction ultrasound tomography using nonuniform FFT." *IEEE Trans Med Imaging*, vol. 21, no. 11 pp. 1395–1401, 2002.