REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
30-06-2010

2. REPORT TYPE
Final Performance Report

3. DATES COVERED *(From-to)*
01-FEB-07 to 31-MAY-10

4. TITLE AND SUBTITLE
Compressive Signal Processing

5a. CONTRACT NUMBER

5b. GRANT NUMBER
FA9550-07-1-0301

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Baraniuk, Richard G.

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Rice University
6100 Main St. MS 16
Houston TX 77005

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Dr. Jon Sjogren
Air Force Office of Scientific Research
875 North Randolph St.
Ste. 325, Room 3112
Arlington VA 22203-1768

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSORING/MONITORING AGENCY REPORT NUMBER

12. DISTRIBUTION AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
In this project, we explored the theory and applications of compressive sensing (CS), in which non-adaptive, linear projections are used to acquire an efficient representation of a compressible signal or image directly using just a few measurements. The signal is then reconstructed by solving a tractable inverse problem. CS offers a fresh approach to framing and solving a number of timely and challenging problems in signal processing that relate directly to operational goals of the Air Force. Our approached was directed along three research thrusts. We first addressed the information scalability of CS. We applied CS principles to classification problems, showed that the CS measurement rate could be decreased with addition signal models, and investigated one-bit compressive sensing. Second, we improved on previous work in distributed compressive sensing. We created a joint manifold signal model, used graphical models to derive performance bounds on multi-sensor settings, and applied distributed CS concepts to a bearing estimation problem. Finally, we created a CS based radar framework and applied it to both 1-D and 2-D problems. Considering RF hardware, we proposed a compressive wide-band signal receiver, and we also used CS concepts for background subtraction.

15. SUBJECT TERMS: compressed sensing, manifolds, dimensionality reduction, random projections, sparsity, manifold learning, image classification, object recognition, smashed filter, radar, graphical models, jointly sparse signals, distributed compressed sensing, wavelets, data fusion, background subtraction, matrix completion, bearing estimation, RF acquisition

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Richard G. Baraniuk
U	U	U	SAR	8	19b. TELEPONE NUMBER (*Include area code*) 713-348-5132

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI-Std Z39-18

Compressive Signal Processing
Final Performance Report

Richard G. Baraniuk

1 Introduction

This is the final performance report for AFOSR Grant FA9550-07-1-0301 *Compressive Signal Processing.* We begin by reviewing the project objectives, and then follow with a comprehensive summary of our most significant achievements. We conclude with a list of publications supported by the grant, and a list of project personnel.

2 Project objectives

This project aimed to explore the foundations and applications of compressive sensing (CS) signal acquisition, analysis, and processing. Specifically, we investigated:

1. **Information scalability of CS** The CS literature has focused almost exclusively on problems in signal reconstruction, approximation, and estimation in noise. However, in many signal processing applications (including most communications and many radar systems), signals are acquired only for the purpose of making a detection or classification decision. We explored the information scalability of CS to a range of statistical inference tasks. Tasks such as detection do not require a reconstruction of the signal, but only require estimates of the relevant sufficient statistics for the problem at hand. We investigated how CS principles can achieve direct detection/recognition from CS measurements without reconstructing the signal/image involved.

2. **Distributed sensing and encoding using CS** The CS literature has focused almost exclusively on problems involving single sensors, signals, or images. However, many important applications involve distributed networks or arrays of sensors. We developed theory and algorithms for distributed compressive sensing (DCS) that enable new signal acquisition and coding algorithms for multi-signal ensembles and sensor networks that exploit both intra- and inter-signal correlation structures.

3. **CS-based radar imaging and processing** We sought to investigate how CS concepts can enable new and simplified kinds of radar imaging hardware and algorithms, anticipating that our techniques will be particularly appropriate for inexpensive networks/arrays of radar receivers.

3 Project accomplishments

3.1 Information scalability of CS

Our research in information scalability of CS followed three different threads. We first investigated the use of compressive measurements for classification decisions, rather than a full reconstruction. The result of our work was the smashed filter, a new tool for compressive classification and recognition. Our second focus was to apply signal models in addition to existing sparsity models to further reduce the number of measurements required for CS. In applying wavelet tree and block sparsity models, we were able to reduce the number of required measurements to the order of signal sparsity. Finally, we pushed CS measurements to their lower limit. We investigated the case of 1-bit measurements, which preserve only the sign information of the random measurements. We demonstrated that this approach performs significantly better compared to the classical compressive sensing reconstruction methods, even as the signal becomes less sparse and as the number of measurements increases.

3.1.1 The smashed filter

CS enables the reconstruction of a sparse or compressible image or signal from a small set of linear, non-adaptive (even random) projections. However, in many applications, including object and target recognition, we are ultimately interested in making a decision about an image rather than computing a reconstruction. We have proposed a framework for compressive classification that operates directly on the compressive measurements without first reconstructing the image. We dub the resulting dimensionally reduced matched filter the smashed filter. The first part of the theory mapped traditional maximum likelihood hypothesis testing into the compressive domain; we found that the number of measurements required for a given classification performance level does not depend on the sparsity or compressibility of the images but only on the noise level. The second part of the theory applied the generalized maximum likelihood method to deal with unknown transformations such as the translation, scale, or viewing angle of a target object. We exploited the fact the set of transformed images forms a low dimensional, nonlinear manifold in the high-dimensional image space. We found that the number of measurements required for a given classification performance level grows linearly in the dimensionality of the manifold but only logarithmically in the number of pixels/samples and image classes. Using both simulations and measurements from a new single-pixel compressive camera, we demonstrated the effectiveness of the smashed filter for target classification using very few measurements. The details of these results appear in [1].

3.1.2 Model based compressive sensing

Standard CS theory dictates that robust signal recovery is possible from $M = O(K \log(N/K))$ measurements, but we have demonstrated that it is possible to substantially decrease M without sacrificing robustness. We accomplished this reduction by leveraging more realistic signal models that go beyond simple sparsity and compressibility, including structural dependencies between the values and locations of the signal coefficients. We introduced a model-based CS theory that parallels the conventional theory and provides concrete guidelines on how to create model-based recovery algorithms with provable performance guarantees. A highlight was the introduction of a new class of structured compressible signals along with a new sufficient condition for robust structured compressible signal recovery that we dub the restricted amplification property (RAmP). The RAmP is the natural counterpart to the restricted isometry property (RIP) of conventional CS. To take practical advantage of the new theory, we integrated two relevant signal models - wavelet trees and block sparsity - into two state-of-the-art CS recovery algorithms and proved that they offer robust recovery from just $M = O(K)$ measurements. Extensive numerical simulations demonstrated the validity and applicability of our new theory and algorithms. The details of these results appear in [2].

3.1.3 One-bit compressive sensing

Compressive sensing reconstruction has been shown to be robust to multi-level quantization of the measurements, in which the reconstruction algorithm is modified to recover a sparse signal consistent to the quantization measurements. We considered the limiting case of 1-bit measurements, which preserve only the sign information of the random measurements. Although it is possible to reconstruct using the classical compressive sensing approach by treating the 1-bit measurements as ± 1 measurement values, we reformulated the problem by treating the 1- bit measurements as sign constraints and further constraining the optimization to recover a signal on the unit sphere. Thus the sparse signal was recovered within a scaling factor. We demonstrated that this approach performs significantly better compared to the classical compressive sensing reconstruction methods, even as the signal becomes less sparse and as the number of measurements increases. The details of these results appear in [3].

3.2 Distributed sensing and encoding using CS

Moving beyond the paradigm single-sensor compressive sensing, we developed theory and algorithms for compressive sensing with multiple sensors. We considered inter-sensor dependencies and created a joint manifold model for distributed compressive sensing. We also addressed the problem of bearing estimation of plane waves. We made a distributed matrix completion framework that reduces inter-sensor communication while maintaining estimation accuracy. Finally, we advanced CS theory in determining performance limits for distributed compressive sensing with graphical model priors.

3.2.1 Data fusion with joint manifolds

The emergence of low-cost sensing architectures for diverse modalities has made it possible to deploy sensor networks that capture a single event from a large number of vantage points and using multiple modalities. In many scenarios, these networks acquire large amounts of very high-dimensional data. For example, even a relatively small network of cameras can generate massive amounts of high-dimensional image and video data. One way to cope with such a data deluge is to develop low-dimensional data models. Manifold models provide a particularly powerful theoretical and algorithmic framework for capturing the structure of data governed by a low-dimensional set of parameters, as is often the case in a sensor network. However, these models do not typically take into account dependencies among multiple sensors. In response, we created a new joint manifold framework for data ensembles that exploits such dependencies. We showed that joint manifold structure can lead to improved performance for a variety of signal processing algorithms for applications including classification and manifold learning. Additionally, recent results concerning random projections of manifolds enabled us to formulate a network-scalable dimensionality reduction scheme that efficiently fuses the data from all sensors. The details of these results appear in [4].

3.2.2 Distributed bearing estimation via matrix completion

We considered bearing estimation of multiple narrow-band plane waves impinging on an array of sensors. For this problem, bearing estimation algorithms such as minimum variance distortion-less response (MVDR), multiple signal classification, and maximum likelihood generally require the array covariance matrix as sufficient statistics. Interestingly, the rank of the array covariance matrix is approximately equal to the number of the sources, which is typically much smaller than the number of sensors in many practical scenarios. In these scenarios, the covariance matrix is low-rank and can be estimated via matrix completion from only a small subset of its entries. We proposed a distributed matrix completion framework to drastically reduce the inter-sensor communication in a network while still achieving near-optimal bearing estimation accuracy. Using recent results in noisy matrix completion, we provided sampling bounds and show how the additive noise at the sensor observations affects the reconstruction performance. We demonstrated via simulations that our approach sports desirable tradeoffs between communication costs and bearing estimation accuracy. The details of these results appear in [5].

3.2.3 Performance limits for jointly sparse signals via graphical models

Existing CS framework has been proposed for efficient acquisition of sparse and compressible signals through incoherent measurements. In previous work, we introduced a new concept of joint sparsity of a signal ensemble. For several specific joint sparsity models, we demonstrated distributed CS schemes. Our most recent contributions considered joint sparsity via graphical models that link the sparse underlying coefficient vector, signal entries, and measurements. Our converse and achievable bounds established that the number of measurements required in the noiseless measurement setting is closely related to the dimensionality of the sparse coefficient vector. Single signal and joint (single-encoder) CS are special cases of joint sparsity, and their performance limits fit into our graphical model framework for distributed (multi-encoder) CS. The details of these results appear in [6].

3.3 CS-based radar imaging and processing

CS principles have enabled new radar imaging hardware and algorithms. In exploring the intersection of CS theory with radar applications, we first formalized our approach to 1-D CS radar and expanded our existing work to a 2-D SAR CS imaging problem. We next applied the concepts of CS to a new, compressive RF receiver. This technology could be incorporated into both radar, as well as more general wideband signal acquisition. And finally, for both radar imaging and wider imaging problems, background subtraction is an important tool for target detection and tracking. We used CS principles to directly recover background subtracted images, requiring fewer measurements than if the entire scene needed to be reconstructed.

3.3.1 Compressive radar imaging

We created a new approach to radar imaging based on the concept CS. We demonstrated that CS has the potential to make two significant improvements to radar systems: (i) eliminating the need for the pulse compression matched filter at the receiver, and (ii) reducing the required receiver analog-to-digital conversion bandwidth so that it need operate only at the radar reflectivity's potentially low "information rate" rather than at its potentially high Nyquist rate. These ideas could enable the design of new, simplified radar systems, shifting the emphasis from expensive receiver hardware to smart signal recovery algorithms. The details of these results appear in [7].

3.3.2 Compressive wide-band RF acquisition

CS exploits the sparsity present in many signals to reduce the number of measurements needed for digital acquisition. With this reduction would come, in theory, commensurate reductions in the size, weight, power consumption, and/or monetary cost of both signal sensors and any associated communication links. We have examined the use of CS in environments where the input signal takes the form of a sparse combination of narrowband signals of unknown frequencies that appear anywhere in a broad spectral band. We formulated the problem statement for such a receiver and establish a reasonable set of requirements that a receiver should meet to be practically useful. The performance of a CS receiver for this application was then evaluated in two ways: using applicable CS theory and using a set of computer simulations carefully constructed to compare the CS receiver against the performance expected from a conventional implementation. This has set the stage for future work that will use these results to produce comparisons of the size, weight, and power consumption of a CS receiver against an exemplar of a conventional design. The details of these results appear it [8].

3.3.3 CS for background subtraction

We have created a method to directly recover background subtracted images using CS, with applications to some communication constrained multi-camera computer vision problems. We showed how to apply the CS theory to recover object silhouettes (binary background subtracted images) when the objects of interest occupy a small portion of the camera view, i.e., when they are sparse in the spatial domain. We casted the background subtraction as a sparse approximation problem and provide different solutions based on convex optimization and total variation. In our method, as opposed to learning the background, we learned and adapted a low dimensional compressed representation of it, which is sufficient to determine spatial innovations; object silhouettes were then estimated directly using the compressive samples without any auxiliary image reconstruction. We also considered simultaneous appearance recovery of the objects using compressive measurements. In this case, we showed that it may be necessary to reconstruct one auxiliary image. To demonstrate the performance of the proposed algorithm, we produced results on data captured using a compressive single-pixel camera. We also illustrated that our approach is suitable for image coding in communication constrained problems by using data captured by multiple conventional cameras to provide 2D tracking and 3D shape reconstruction results with compressive measurements. The details of these results appear it [9].

4 Publications supported by this grant

2007

R. Neelamani, M. Deffenbaugh, and R. G. Baraniuk, "Texas Two-Step: A Framework for Optimal Multi-Input Single-Output Deconvolution," IEEE Transactions on Signal Processing, October 2007.

R. G. Baraniuk, "Compressive Sensing," Lecture Notes in IEEE Signal Processing Magazine, Vol. 24, No. 4, pp. 118120, July 2007.

R. Neelamani, S. Dash, and R. G. Baraniuk, "On Nearly Orthogonal Lattice Bases and Random Lattices," SIAM Journal on Discrete Mathematics, Vol. 21, No. 1, pp. 199-219, 2007.

C. J. Rozell, D. H. Johnson, R. G. Baraniuk, B. A. Olshausen, "Locally Competitive Algorithms for Sparse Approximation," IEEE International Conference on Image Processing, ICIP-2007, San Antonio, TX, September 2007.

M. Duarte, M. Davenport, M. Wakin, J. Laska, D. Takhar, K. F. Kelly, R. G. Baraniuk, "Multiscale Random Projections for Compressive Classification," IEEE International Conference on Image Processing, ICIP-2007, San Antonio, TX, September 2007.

M. Sheikh, R. G. Baraniuk, "Blind Error-free Detection of Transform-Domain Watermarks," IEEE International Conference on Image Processing, ICIP-2007, San Antonio, TX, September 2007.

P. T. Boufounos, M. F. Duarte, and R. G. Baraniuk, "Sparse Signal Reconstruction from Noisy Compressive Measurements Using Cross Validation," IEEE Statistical Signal Processing Workshop, Madison, WI, August, 2007.

M. Davenport, R. G. Baraniuk, and C. Scott, "Minimax support vector machines," IEEE Statistical Signal Processing Workshop, Madison, WI, August, 2007.

M. A. Sheikh, S. Sarvotham, O. Milenkovic, and R. G. Baraniuk, "DNA Array Decoding From Nonlinear Measurements By Belief Propagation," IEEE Statistical Signal Processing Workshop, Madison, WI, August, 2007.

M. Moravec, J. Romberg, R. G. Baraniuk, "Compressive Phase Retrieval," Wavelets XII in SPIE International Symposium on Optical Science and Technology, San Diego, August 2007.

P. Boufounos, R. G. Baraniuk, "Sigma Delta Quantization for Compressive Sensing," Wavelets XII in SPIE International Symposium on Optical Science and Technology, San Diego, August 2007.

T. Ragheb, S. Kirolos, J. Laska, A. Gilbert, M. Strauss, R. G. Baraniuk, Y. Massoud, "Implementation Models for Analog-to-Information Conversion via Random Sampling," IEEE International Midwest Symposium on Circuits and Systems, Montreal, August 2007.

J. N. Laska, S. Kirilos, M. F. Duarte, T. Ragheb, R. G. Baraniuk, Y. Massoud, "Theory and Implementation of an Analog-to-Information Converter using Random Demodulation," IEEE International Symposium on Circuits and Systems (ISCAS), New Orleans, May 2007.

W. L. Chan, M. L. Moravec, R. G. Baraniuk, and D. M. Mittleman, "Terahertz Imaging with Compressed Sensing and Phase Retrieval," Conference on Lasers and Electro-Optics (CLEO), San Jose, May 2007.

R. G. Baraniuk and T. P. H. Steeghs, "Compressive Radar Imaging," IEEE Radar Conference, Waltham, MA, April 2007.

C. J. Rozell, D. H. Johnson, R. G. Baraniuk, B. A. Olshausen, "Neurally Plausible Sparse Coding via Competitive Algorithms," Computational and Systems Neuroscience (Cosyne), Salt Lake City, UT, February 2007.

M. A. Davenport, M. F. Duarte, M. B. Wakin, J. A. Laska, D. Takhar, K. F. Kelly, R. G. Baraniuk, "The Smashed Filter for Compressive Classification and Target Recognition,"IS&T/SPIE Computational Imaging IV, San Jose, January 2007.

2008

P. Boufounos and R.G. Baraniuk, "1-Bit Compressive Sensing," Proc. 42nd annual Conference on Information Sciences and Systems (CISS) 2008, March 19-21 2008, Princeton, NJ.

P. Boufounos and R.G. Baraniuk, "Reconstructing Sparse Signals From their Zero Crossings," Proceedings of the International Conference on Acoustics, Speech, and Signal Processing (ICASSP), 2008, Las Vegas, NV.

V. Cevher, M. F. Duarte, and R. G. Baraniuk, "Distributed target localization via spatial sparsity," EUSIPCO 2008, Lausanne, Switzerland, 25-29 August 2008.

V. Cevher, A. C. Sankaranarayanan, M. F. Duarte, D. Reddy, R. G. Baraniuk, and R. Chellappa, "Compressive sensing for background subtraction," ECCV, Marseille, France, 12-18 October 2008.

M. F. Duarte, M. A. Davenport, D. Takhar, J. N. Laska, T. Sun, K. F. Kelly and R. G. Baraniuk, "Single Pixel Imaging via Compressive Sampling," IEEE Signal Processing Magazine, Vol. 25, No. 2, pp. 83-91, March 2008.

M. F. Duarte, S. Sarvotham, D. Baron, M. B. Wakin and R. G. Baraniuk, "Performace Limits for Jointly Sparse Signals via Graphical Models," Proceedings of the Sensor, Signal and Information Processing (SenSIP) Workshop, 2008, Sedona, AZ.

M. F. Duarte, M. B. Wakin and R. G. Baraniuk, "Wavelet-Domain Compressive Signal Reconstruction Using a Hidden Markov Tree Model," Proceedings of the International Conference on Acoustics, Speech, and Signal Pro-

cessing (ICASSP), 2008, Las Vegas, NV. pp. 5137-5140.

V. Cevher, M. F. Duarte, C. Hegde, and R. G. Baraniuk, “Sparse Signal Recovery Using Markov Random Fields,” Proceedings of the Workshop on Neural Information Processing Systems (NIPS), Vancouver/Canada, Dec. 2008.

2009

V. Cevher, P. T. Boufounos, R. G. Baraniuk, A. C. Gilbert, and M. J. Strauss, “Near-optimal Bayesian localization via incoherence and sparsity,” IPSN 2009, San Francisco, CA/USA, Apr. 2009.

V. Cevher, P. Indyk, C. Hegde, and R. G. Baraniuk, “Recovery of Clustered Sparse Signals from Compressive Measurements,” Sampling Theory and Applications (SAMPTA), Marseille, May 2009.

M. A. Davenport, and R. G. Baraniuk, “Sparse geodesic paths,” AAAI Fall 2009 Symposium on Manifold Learning, Arlington, Virginia, Nov. 2009.

M. A. Davenport, P. T. Boufounos, and R. G. Baraniuk, “Compressive domain interference cancellation,” Workshop on Signal Processing with Adaptive Sparse Structured Representations (SPARS), Saint-Malo, France, Apr. 2009.

M. F. Duarte, V. Cevher, and R. G. Baraniuk, “Model-based compressive sensing for signal ensembles,” Proceedings of the 47rd Allerton Conference on Communication, Control, and Computing, Monticello, IL, Sep. 2009.

M. F. Duarte, C. Hegde, V. Cevher, and R. G. Baraniuk, “Recovery of Compressible Signals in Unions of Subspaces,” Proceedings of the Conference on Information Sciences and Systems (CISS), Baltimore, MD/USA, Mar. 2009.

C. Hegde, and R. G. Baraniuk, “Compressive Sensing of Streams of Pulses,” Allerton Conference on Communication, Control, and Computing, Sep. 2009.

C. Hegde, M. F. Duarte, and V. Cevher, “Compressive Sensing Recovery of Spike Trains Using Structured Sparsity,” Proceedings of the Workshop on Signal Processing with Adaptive Sparse Representations (SPARS), Saint Malo, France, Apr. 2009.

J. N. Laska, P. T. Boufounos, and R. G. Baraniuk, “Finite Range Scalar Quantization for Compressive Sensing,” Proc. International Conference on Sampling Theory and Applications (SAMPTA), Marseille, May 2009.

J. N. Laska, M. A. Davenport, and R. G. Baraniuk, “Exact signal recovery from sparsely corrupted measurements through the pursuit of justice,” Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, California, Nov. 2009.

J. Treichler, M. A. Davenport, and R. G. Baraniuk, “Application of compressive sensing to the design of wideband signal acquisition receivers,” 6th U.S. / Australia Joint Workshop on Defense Applications of Signal Processing (DASP), Lihue, Hawaii, Sept. 2009.

2010

Baraniuk, R. G., V. Cevher, M. F. Duarte, and C. Hegde, “Model-based Compressive Sensing,” to appear in IEEE Transactions in Information Theory, 2010.

Baraniuk, R. G., V. Cevher, and M. B. Wakin, “Low-dimensional models for dimensionality reduction and signal recovery: A geometric perspective,” to appear in Proceedings of the IEEE, 2010.

Davenport, M. A., C. Hegde, M. F. Duarte, and R. G. Baraniuk, “Joint Manifolds for Data Fusion,” to appear in IEEE Transactions on Image Processing, 2010.

Waters, A., and V. Cevher, “Distributed Bearing Estimation via Matrix Completion,” IEEE International Confer-

ece on Acoustics, Speech, and Signal Processing (ICASSP), Dallas, Texas, March, 2010.

Schnelle, S. R., J. N. Laska, C. Hegde, M. F. Duarte, M. A. Davenport, and R. G. Baraniuk, "Texas Hold 'Em Algorithms for Distributed Compressive Sensing," IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), Dallas, TX, Mar., 2010.

Davenport, M. A., P. T. Boufounos, M. B. Wakin, and R. G. Baraniuk, "Signal processing with compressive measurements," Journal of Selected Topics in Signal Processing, vol. 4, no. 2, pp. 445-460, Apr., 2010.

5 Professional personnel

Principal Investigator
Richard G. Baraniuk

Postdoctoral Research Associates
Petros Boufounos, Volkan Cevher, Jarvis Haupt, Aswin Sankaranarayanan

Graduate Student Research Assistants
Mark Davenport, Marco Duarte, Chinmay Hegde, Jason Laska, Matthew Moravec, Manjari Narayan, Mona Sheikh, Andrew Waters

References

[1] M. A. Davenport, M. F. Duarte, M. B. Wakin, J. N. Laska, D. Takhar, K. F. Kelly, and R. G. Baraniuk, "The smashed filter for compressive classification and target recognition," in *Proceedings of Computational Imaging V at SPIE Electronic Imaging*, (San Jose, CA), Jan. 2007.

[2] R. G. Baraniuk, V. Cevher, M. F. Duarte, and C. Hegde, "Model-based compressive sensing," *to appear in IEEE Transactions in Information Theory*, 2010.

[3] P. T. Boufounos and R. G. Baraniuk, "One-bit compressive sensing," in *Conference on Information Sciences and Systems (CISS)*, (Princeton), March 2008.

[4] M. A. Davenport, C. Hegde, M. F. Duarte, and R. G. Baraniuk, "Joint manifolds for data fusion," *to appear in IEEE Transactions on Image Processing*, 2010.

[5] A. Waters and V. Cevher, "Distributed bearing estimation via matrix completion," in *IEEE International Conferece on Acoustics, Speech, and Signal Processing (ICASSP)*, (Dallas, Texas), March 2010.

[6] M. F. Duarte, S. Sarvotham, D. Baron, M. B. Wakin, and R. G. Baraniuk, "Performance limits for jointly sparse signals via graphical models," in *Proceedings of the Sensor, Signal and Information Processing (SenSIP) Workshop*, (Sedona, AZ), May 2008.

[7] R. G. Baraniuk and P. Steeghs, "Compressive radar imaging," in *IEEE Radar Conference*, (Waltham, MA), Apr. 2007.

[8] J. Treichler, M. A. Davenport, and R. G. Baraniuk, "Application of compressive sensing to the design of wideband signal acquisition receivers," in *6th U.S. / Australia Joint Workshop on Defense Applications of Signal Processing (DASP)*, (Lihue, Hawaii), Sept. 2009.

[9] V. Cevher, A. C. Sankaranarayanan, M. F. Duarte, D. Reddy, R. G. Baraniuk, and R. Chellappa, "Compressive sensing for background subtraction," in *Proceedings of the European Conference on Computer Vision (ECCV)*, (Marseille/France), pp. 155–168, Oct. 2008.