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14. ABSTRACT

In this final report, several questions in information fusion and compression are answered: (1) The generalized likelihood ratio for fusing the several time series in a distributed array of sensors, to detect dependence, is a generalized Hadamard ratio; under the null hypothesis of independence of Gaussian time series, the statistic is distributed as a product of independent beta random variables; in the limit of long observation times, the statistic is a broadband coherence; (2) the fusion and compression of noisy sensor measurements, for power-limited transmission over a noisy channel, consists of a transformation of measurements into canonical coordinates, scaling, and rotation; there is a water-filling interpretation; (3) the optimum design of a linear secondary channel of measurements to fuse with a primary linear channel of measurements maximizes a generalized Rayleigh quotient; (4) the asymptotically optimum threshold setting at a local detector in a sensor array is determined by a one-dimensional search on a Receiver Operating Characteristic that maximizes a Kullback-Leibler distance; the threshold setting that maximizes a mutual information is a useful approximation; (5) a greedy rule for fusing and compressing vector-valued measurements into scalars simply

15. SUBJECT TERMS

Information fusion, measurement compression, multi-sensor array, noisy sensor, noisy channel, time series, Hadamard ratio, broadband coherence, canonical coordinates, water-filling, large deviations, receiver operating characteristic; probability of error, signal-to-noise ratio, greedy compression, Kullback-Leibler distance.

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Information Fusion from the Point of View of Communication Theory

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August 19, 2013

Contents

1 Objectives

Objectives are little changed from the originally proposed objectives: derive algorithms for fusion and compression of measurements in coherent and distributed sensor arrays, with a view to trading off resolution, performance and signal-to-noise ratio.

2 Status of Effort: Executive Summary of Accomplishments

During this 3-year research program we have answered a number of fundamental questions in information fusion, using the methods and insights of communication theory:

1. How are the several time series in a sensor suite to be fused when determining whether or not the time series are linearly dependent, and what is the distribution of the fused statistic? The generalized likelihood ratio statistic for this problem is a generalized Hadamard ratio. Under the null hypothesis that the Gaussian time series are linearly independent, this Hadamard ratio is distributed as the product of independent beta random variables. When the individual time series are wide sense stationary, and in the limit as the length of each time series grows without bound, the Hadamard ratio is a *broadband coherence*, consisting of narrowband coherences fused over a broad band of frequencies.

2. How are measurements to be fused into a compressed set of measurements which maximize the rate at which compressed measurements can bring information about a physical state? What is the influence of dimension reduction on the information rate? The compressor that maximizes information rate consists of dimension reduction in a system of *scaled and rotated canonical coordinates*. Moreover, there is a water-filling rule for selecting the dimension, under a power constraint.

3. How is a secondary channel of measurements to be designed and fused with an existing primary channel of measurements to maximize the rate at which the two channels bring information about an underlying primary state? For an important class of models, the secondary channel maximizes a generalized Rayleigh quotient, and it has a water-filling interpretation. A power constraint limits the dimension of the secondary channel.

4. How are measurements to be detected and then fused in a sensor suite to detect a common target? What is the asymptotic probability of error for the optimum fusion? The asymptotically optimum threshold at each sensor is determined by the operating point on an ROC that maximizes the error exponent in a large deviations solution for the probability of error. A sub-optimum solution that maximizes mutual information between the binary output of each sensor and the random binary hypotheses is a useful approximation.

5. Is there a greedy policy for compressing a sequence of vector-valued measurements into a sequence of scalar measurements that maximize information gain at each compression? When the measurements are linear maps of an underlying Gaussian state, and the measurement noise is white, the policy selects compressors from pre-computed eigenvectors of a prior covariance, according to eigenvalues of a posterior covariance. Performance at a given number of scalar compressions is nearly as good as the performance of a globally optimum policy for many illustrative problems.

where the $L \times L$ matrix $S(e^{j\theta})$ is the cross spectral matrix between the L time series, estimated from M realizations of them. These two forms of multichannel coherence are invariant to uncoupled linear transformations of the time series, and describe for the first time what it means to fuse narrowband coherences of the form $S_{mn}(e^{j\theta})$, at frequency θ, into a broadband coherence among L channels. The key is to integrate the logarithm of narrowband coherence over the Nyquist band of frequencies.

Applications of These Results. This result applies to the detection of linearly-dependent time series in a sensor array. Typically the linear dependence reveals the presence of one or more sources of radiation or vibration, as in radar, sonar, wireless communication, ground-sensing, geophysics, or machine monitoring. For example, in cognitive, ad-hoc, radio, where the problem is to detect the presence or absence of radiation in a particular licensed band, this detector determines when a band is free for use. In radar, sonar, ground-sensing, and machine-monitoring the detector is used to detect propagating radiation or vibration.

Extensions and Future Work. An important and useful extension is to the case where the alternative hypothesis consists of *periodically-correlated* time series, as in periodically-modulated data transmissions. This would make the results directly applicable to signal intelligence. When the radiation or vibration to be detected is bandlimited, as in radar and machine monitoring, then the detector formula should be modified, from first principles, to account for band-limiting and band-shaping.

3.2 Scaled and Rotated Canonical Coordinates for Fusion and Compression of Noisy Sensor Measurements

In references [8], [9], [12] we have addressed the problem of compressing noisy sensor measurements into a small number of fused statistics, which are to be transmitted under a power constraint over a noisy channel. This is *the* general compression problem, and it subsumes precoding and reduced-rank filtering as special cases.

The Problem. An imperfect sensor produces a noisy and linearly transformed copy of a vector-valued signal of interest. This measurement is to be compressed into a lower dimensional measurement, for transmission over a noisy channel. The problem subsumes the special cases of reduced-rank filtering (the channel noise is zero) and precoding (the sensor noise is zero). As a measure of performance one can consider the trace of the error covariance matrix when estimating the signal of interest from the noisy channel measurement, or its determinant.

Main Results. The solution for fusion and compression that minimizes the determinant of the error covariance matrix consists of transformation of the sensor measurement into *canonical coordinates*, *scaling* of these coordinates, and transformation of these *scaled canonical coordinates* into the sub-dominant modes of the channel transmittance matrix. That is, the signal transmitted over the channel is

$$z = U\Gamma w, \; w = G^T Q_{yy}^{-1/2} y \tag{4}$$

In this equation, the sensor measurement $y \in \mathscr{R}^n$ is a noisy and linearly transformed function of the signal $x \in \mathscr{R}^m$ of interest, and the transmitted signal $z \in \mathscr{R}^r$ is carried on the sub-dominant orthogonal channel modes $U \in \mathscr{R}^{n\times r}$ of the channel. The measurement $w = G^T Q_{yy}^{-1/2} y$ is the sensor measurement y, resolved into its canonical coordinates, and the measurement Γw is the sensor measurement resolved into its r dominant *scaled* canonical coordinates. The diagonal scaling matrix Γ is a function of canonical coordinates, channel noise variances, and the power limitation on the transmitted signal z.

The net consequence of dimension reduction to r scaled and rotated canonical coordinates is that the volume of the error covariance for estimating the signal x from the noisy channel transmission $z+n$ is

$$\det[Q_{ee|z+n}] = \det[Q_{xx|y}] \prod_{r+1}^{min(m,n)} \frac{1}{1-k_i^2} \prod_{i=1}^{r} (1+\beta_i^2) \tag{5}$$

The terms in this formula are illuminating: $\det[Q_{xx|y}]$ is the volume of the error concentration ellipse with no compression or transmission over the noisy channel; $\prod_{r+1}^{min(m,n)} \frac{1}{1-k_i^2}$ inflates this volume by discarding canonical coordinates, and $\prod_{i=1}^{r}(1+\beta_i^2)$ inflates the volume by channel effects.

Applications of these Results. This is the general problem of fusing and compressing a noisy sensor measurement into a bandwidth-efficient measurement for transmission over a noisy channel. As such it addresses fusion and compression in its most general form, making it applicable to networks of electromagnetic or acoustic sensors.

Extensions and Future Work. These results are parametric, in the sense that they depend on second-order characterizations of the sensor and the channel. So what is the sensitivity of the solution to mismatch between the assumed second-order statistics and the actual? What can be said about adaptive versions of these results that would use estimates of second-order statistics? How does the performance of random compressions that use no second-order information compare with these second-order designs? Can this second-order theory be extended to a higher-order theory through the use of kernel methods, and if so, how are kernels to be selected and what are the compressed variables?

3.3 Fusing a Secondary Measurement Channel with a Primary Channel

In references [10], [11], [12] we have addressed the problem of designing and fusing a secondary channel of measurements with an existing primary channel, in order to improve estimator performance over what can be achieved with the existing primary channel only. The motivating problem is to fuse measurements of one sensing modality with measurements of another modality.

The Problem. An existing primary sensor returns measurements which are noisy linear transformations of a primary signal. A secondary sensor is to be designed to bring a noisy linear transformation of a secondary signal that is known to be correlated with the primary signal. The outputs of the primary and secondary sensor channels are to be fused to improve estimation of the primary signal. The question is how to design the secondary sensor, under a power constraint, to augment the primary sensor. The objective is to decrease the volume of the error concentration ellipse for the primary signal.

Main Results. In the case of a scalar-valued secondary channel, the optimum secondary channel maximizes a standard Rayleigh quotient. More generally, when the secondary channel carries a linear version of the signal in the primary channel, plus white noise, the solution for the linear map G of the secondary channel maximizes the generalized Rayleigh quotient [10], [11]

$$D(G) = \frac{1}{2}\log\det[I + Q_{\xi\xi}^{-1/2} Q_{\omega\omega} Q_{\xi\xi}^{-1/2}] \tag{6}$$

where $Q_{\xi\xi}$ the covariance of what might be called noise and $Q_{\omega\omega}$ is the covariance of the signal component of the secondary channel that brings information about the primary signal. Both covariances depend on the secondary channel matrix G. There is an analytical, water-filling, solution. For more general problems, we propose two numerical algorithms to approximate the optimal design, one of which exploits the geometry of the unit sphere and the other of which does not enforce this geometry, but enforces the power constraint after each step of the algorithm. A discussion of the choice of dimension for the secondary channel is given.

Applications of these Results. These results give a framework for designing and fusing a secondary measurement channel and determining when the design of such a secondary channels brings enough extra performance gain to warrant the effort. By considering practical problems for which channel matrices and noises can be characterized, these results can guide the decision of whether or not to design and fuse.

Extensions and Future Work. The theory we have developed so far requires linear sensors. When sensors return detected measurements, as opposed to complex measurements, then the theory would require modification to account for nonlinearities.

3.4 Globally Optimum Fusion in Distributed Sensor Networks

In references [13], [14], [15] we consider the problem of setting local decision thresholds in a sensor suite that is designed to test the presence or absence of a radiating or scattering signal in its environment. Each sensor makes a binary decision. Each decision is unreliable and governed by a Receiver Operating Characteristic (ROC), which is determined by physics and electronics. At a fusion center, binary decisions from each sensor are fused into a global decision about the presence or absence of a signal.

The Problem. The problem is to determine the optimum threshold setting, or equivalently the optimum operating point on the ROC of each sensor, for optimum performance of the globally-fused decision. Performance is measured by probability of error.

Main Results. We have derived two thresholds: the threshold that maximizes mutual information between the sensor decision (a binary random variable) and the hypothesis (a binary random variable), and the threshold that maximizes the error exponent in a large deviations formula for probability of error. Each of these is found with a simple one-dimensional search along the ROC curve for the local detector. Each of these thresholds outperforms previously-derived ad-hoc solutions to this problem. The key formula for the asymptotically (in the number of sensors) optimum operating point (P_f^*, P_d^*) on the ROC is

$$(P_f^*, P_d^*) = argmax_{(P_f, P_d)} D_{KL}\left(\frac{1}{1 + \frac{\log(P_f/P_d)}{\log(1-P_d)/(1-P_f)}} || P_f\right) \tag{7}$$

where D_{KL} is the Kullback-Leibler distance $D_{KL}(a,b) = alog(a/b) + (1-a)log(1-a)/(1-b)$.

This large deviation (LD) solution for the local threshold has a number of nice features:

- The asymptotically optimal local decision strategy is independent of the total number of sensors L and the priori probabilities that the signal will be present or absent. It depends only on the ROC that governs each sensor.
- Asymptotically, the large deviations solution is minimax. In other words, the LD solution has a constant error exponent under any apriori probabilities of the null and alternative hypotheses.
- As the pair (Pf, Pd) is constrained by the ROC of the local detectors, the search for a maximum of Kullback-Leibler divergence is a one-dimensional search that can be implemented by scanning through detector thresholds.

Applications of these Results. These results are generally applicable to threshold setting in large distributed sensor arrays, requiring only the theoretical or experimental specification of the common ROC for each sensor. They render moot any discussion of the ad-hoc solutions previously proposed. The thresholds for maximizing local mutual information are near enough to optimum to suggest that this principle might be more generally applicable for setting detection thresholds in related problems.

Extensions and Future Work. The natural extension of these results is to multiple hypothesis testing problems, where the aim is to classify signals measured in a sensor array, rather than simply to detect them. The calculation of mutual information becomes more challenging, but the use of large deviations to derive thresholds might still produce tractable results.

3.5 Greedy Fusion and Compression in Signal-Plus-Noise Models

Multiple snapshots of a noisy, vector-valued signal are measured. What is the optimum greedy rule for compressing each vector into a scalar, when the objective is to maximize information gain at each compression?

The problem. A sensor returns a sequence of noisy, vector-valued measurements, each of which is to be fused into a scalar linear statistic. The objective at each fusion is to maximize information gained about the underlying physical state that produced the vector-valued measurements.

Main Results. When the measured signal is Gaussian and the measurement noise is white Gaussian, the answer is that the optimum scalar statistic is an inner product between the measurement and an eigenvector of an apriori signal covariance. That is, the greedy scalar measurement $z_k = a_k^T y_k$, where $y_k = Hx + n_k$, is determined by the a_k that maximizes the Rayleigh quotient [16], [17]

$$R = \frac{a_k^T H P_{k-1} H^T a_k}{||a_k||^2 + \sigma^2} \tag{8}$$

In this equation P_{k-1} is the error covariance for estimating the state x from all previous greedy compressions and $\sigma^2 I$ is the covariance of each of the iid white noises n_k. The eigenvectors of $HP_{k-1}H^T$ are those of HP_0H^T, so the policy for selecting which eigenvector to use at a particular stage of the fusions depends only on the eigenvalues of the posterior covariance $HP_{k-1}H^T$. The key result is that eigenvectors may be computed apriori and eigenvalues may be easily updated to compute the selection policy. There is a water-filling interpretation. Performance is very close to optimum, even though generally sub-optimum.

Applications of these Results. These results apply to any monitoring or data collection problem where multiple measurements may be made of a stationary physical system. These multiple measurements may then be dramatically compressed with linear fusions to achieve performance near to that of an optimum fusion that would treat the sequence of vector-valued measurements as one large vector to be compressed. The only qualifier is that additive noise in each measurement is assumed to be white.

Extensions and Future Work. We do not yet know how colored noise at each vector-valued measurement will affect the near optimality of our results. This is a question worth answering.

3.6 Resolving Hypotheses with Multiple Sensors: The Tradeoff between SNR, Resolution, and Probability of Error

It is a commonplace to resolve questions at increasingly fine levels of resolution. But this raises the question of how finely hypotheses can be resolved, when there is a signal-to-noise ratio budget and a constraint that the probability of error not exceed a specified value. So, what is the tradeoff between resolution, SNR, and $P(E)$, when making measurements in an n sensor array? In references [18], [19], we address and answer this question.

The Problem. Consider a sensor suite in which each measurement consists of a linearly transformed state variable plus additive, possibly non-Gaussian noise. We are interested in how finely the state variable can be resolved subject to a constraint on the probability of error. We then investigate the tradeoffs among signal-to-noise ratio (SNR), desired error probability, and the number of hypotheses to be resolved.

Main Results. We give formulas that show how the SNR required to resolve $M = 2^L$ hypotheses at a specified probability of error $P(E)$ scales with M, and how the number of resolvable hypotheses M at a given error probability $P(E)$ scales with the available SNR. The key formula is

$$L \leq \frac{1}{2}\log_2 SNR - \log_2 G_n^+(P(E)) \quad (9)$$

Here $\frac{1}{2^L}$ is the granularity of resolution per dimension of the underlying p-dimensional parameter space, SNR is signal-to-noise ratio, and G_n is a non-increasing function of the specified probability of error, indexed by the n, the number of sensors that are making d-dimensional measurements of the p-dimensional parameter. By fixing two of the three parameters, L, SNR, and $P(E)$, the third may be solved for, thus providing the trade-off between resolution, signal-to-noise ratio, and probability of error.

Applications of these Results. These results establish the tradeoff among SNR, probability of error, and resolution level for a large class of multi-sensor detection problems. To this extent, the results comprise design rules for the number of sensors, dimensionality of the sensor measurements, and the SNR required to resolve hypotheses about a state variable at a specified probability of error. The sensor suite may be a radar suite, a suite of hyper-spectral imagers, a suite of acoustic sensors, etc.

Extensions and Future Work. To this point, the map from parameter to measurement is given and known. However, there are other possibilities. For example, we could view the map as a precoding matrix to be designed. How should we do this for minimum probability of error? Alternatively, the linear map could be viewed as a channel matrix to be estimated. How would this impact the probability of error or the scaling laws?

3.7 Optimization of Exponential Error Rates for a Suboptimum Fusion Rule in Wireless Sensor Networks

A simple fusion rule in a multi-sensor suite would average M-ary decisions from individual sensors to classify a target in the environment. The decisions are, themselves, transmitted imperfectly over a noisy channel to a fusion center. The question is whether thresholds may be set locally and globally to ensure exponential decay in error probability as the number of sensors grows large. Perhaps there is a threshold that maximizes the error exponent. In references [20], we show that thresholds may be set, optimally.

The Problem. Consider a wireless sensor network used to make a decision about an M-ary hypothesis testing problem. In this system, the kth sensor (out of n) uses its measurement to generate an M-ary message U_k to be sent over its own channel to the fusion center, where U_k is decoded as L_k. In contrast to the common assumption that the data is conditionally independent *and identically distributed*, we assume only conditional independence under each hypothesis. This allows us to model situations in which different sensors have different local detection probabilities as well as situations in which different sensors have communication links of different qualities or signal-to-noise ratios (SNRs). We study the performance of a simple fusion rule that compares the numerical average of the decoded messages to a sequence of thresholds.

Main Results. In [20], [**?**] we prove a theorem that says we can select the thresholds independently in a manner that maximizes the asymptotic decay rate of the average probability of error. Furthermore, it is easy to compute these individual thresholds numerically.

Applications of these Results. These results apply to any network of sensors, each of which makes an M-ary decision, to be transmitted unreliably over an imperfect channel.

Extensions and Future Work. The results in [20], [**?**] require knowledge of the moment generating functions of the channel outputs given the sensor outputs for each class of sensor/channel pair. We conjecture that by developing upper and lower bounds on these functions, we can obtain suboptimal thresholds that require less information about the sensors and channels. This would make the results applicable to problems where little is known about an imperfect channel.

4 Personnel Supported or Associated with this Research Effort

These are the faculty and graduate students who have been supported or associated with this research effort.

- Louis Scharf, Research Professor of Mathematics and PI, Colorado State University, Fort Collins, CO (supported)
- Haonan Wang, Associate Professor of Statistics and co-PI, Colorado State University, Fort Collins, CO (supported)
- J.A. Gubner, Professor of Electrical and Computer Engineering, University of Wisconsin, Madison, WI (associated)
- Yuan Wang, PhD Student in Statistics, Colorado State University, Fort Collins, CO (supported)
- Mahmood Azimi-Sadjadi, Professor of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO (associated)
- Nickolas Klausner, PhD Student in Electrical and Computer Engineering, Colorado State University, Fort Collins, CO (associated)
- Ignacio Santamaria, Professor of Communication Engineering, University of Cantabria, Santander, Spain (associated)
- Javier Via, Professor of Communication Engineering, University of Cantabria, Santander, Spain (associated)
- David Ramirez, PhD Student, University of Cantabria, Santander, Spain and Post-Doctoral Student, University of Paderborn, Paderborn, Germany
- Liuqing Yang, Associate Professor of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO (associated)

- Dongliang Duan, PhD Student, Electrical and Computer Engineering and Assistant Professor of Electrical and Computer Engineering, University of Wyoming, Laramie, WY (associated)
- Edwin Chong, Professor of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO (associated)
- Entao Liu, Post-Doctoral Student, Electrical and Computer Engineering, Colorado State University, Fort Collins, CO (associated)
- Douglas Cochran, Professor of Electrical and Computer Engineering, Arizona State University, Tempe, AZ

5 Publications

These are publications supported by, or in part by, AFOSR. Bold letters indicate that the co-author participated or presented at the conference or workshop

- D. Ramirez, J. Via, I. Santamaria, and L.L. Scharf, "Locally Most Powerful Invariant Tests for Correlation and Sphericity of Gaussian Vectors," IEEE Trans Inform Theory, vol. 59, no. 4, pp 2128-2141 (Apr 2013).
- **D. Ramirez**, J. Iscar, J. Via, I. Santamaria, and L.L. Scharf, "The Locally Most Powerful Invariant Test for Detecting a Rank-P Gaussian Signal in White Noise," IEEE Workshop on Sensor Array and Multichannel (SAM) Signal Processing, 2012.
- **D. Ramirez**, J. Via, I. Santamaria, and **L.L. Scharf**, "Multiple-Channel Detection of a Gaussian Time Series over Frequency-Flat Channels," IEEE Intern Conf on Acoust, Speech, and Signal Processing, Prague, May 22-27, 2011.
- D. Ramirez, J. Via, I. Santamaria, and L.L. Scharf, "Multi-Sensor Beamsteering based on the Asymptotic Likelihood for Colored Signals," IEEE Workshop on Statistical Signal Processing, Nice, July, 2011.
- D. Ramirez, J. Via, I. Santamaria, and L.L. Scharf, "Detection of Spatially-Correlated Gaussian Time Series," IEEE Trans Signal Processing, vol 58, no 10, pp 5006-5015, 2010.
- N. Klausner, M.R. Azimi-Sadjadi, **L.L. Scharf**, and **D. Cochran**, "Space-time Coherence and its Null Distribution," IEEE Conf on Acoustics, Speech, and Signal Processing (ICASSP), Vancouver, BC, May 2013.
- N. Klausner, M.R. Azimi-Sadjadi, and L.L. Scharf, "Detection of Spatially Correlated Time Series from a Network of Sensor Arrays," IEEE Trans Signal Processing, submitted March 2013 and revised Aug. 6, 2013.
- Y. Wang, H. Wang, and L.L. Scharf, "Optimal Compression of a Noisy Measurement for Transmission over a Noisy Channel," IEEE Trans Signal Processing, submitted April 2013.

- **Y. Wang**, H. Wang, and **L.L. Scharf**, “Scaled Canonical Coordinates for Compression and Transmission of Noisy Sensor Measurement,”Asilmar Conf on Signals, Systems, and Computers, Pacific Grove, accepted and to be presented Nov 3-6, 2013.

- Y. Wang, H. Wang, and **L.L. Scharf**, “Fusion Inspired Channel Design,” IEEE International Conf on Acoustics, Speech, and Signal Processing, Vancouver, BC, May 2013.

- Y. Wang, H. Wang, and L.L. Scharf, “The Geometry of Fusion-Inspired Channel Design,” Signal Processing, submitted June 2013.

- Yuan Wang, Linear System Design for Fusion and Compression, PhD Dissertation, Colorado State University, Fort Collins, Aug. 2013.

- **D. Duan**, L. Yang, and **L.L. Scharf**, “The Optimal Fusion Rule for Cooperative Spectrum Sensing from a Diversity Perspective,” Proc. 46th Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, Nov 4-7, 2012.

- D. Duan, L. Yang, and **L.L. Scharf**, “Optimal Local Detection for Sensor Fusion by Large Deviations Analysis,” European Signal Processing Conference (EUSIPCO), Bucharest, Romania, Aug 27-31, 2012.

- D. Duan, L. Yang, and L.L. Scharf, “A Large Deviation (LD) Solution for Globally Optimum Sensor Fusion,” IEEE Trans Signal Processing, submitted Oct 2012 and in revision.

- **E. Liu**, E.K.P. Chong, and **L.L. Scharf**, “Greedy Adaptive Measurements with Signal and Measurement Noise,” Proc. 46th Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, Nov 4-7, 2012.

- E. Liu, E.K.P. Chong, and L.L. Scharf, ”Greedy Adaptive Compression in Signal-Plus-Noise Models,” IEEE Trans Inform Theory, submitted, July 2012 and re-submitted, June 2013.

- **J.A. Gubner** and **L.L. Scharf**, “Resolving a Variable Number of Hypotheses with Multiple Sensors, IEEE Workshop on Statistical Signal Processing, 2012, IEEE Workshop on Statistical Signal Processing, Ann Arbor, MI, Aug 5-8, 2012.

- J.A. Gubner and L.L. Scharf, “Resolving Hypotheses with Multiple sensors: The Tradeoff between SNR, Resolution, and Probability of Error,” IEEE Trans Inform Theory, to be submitted Aug 2013.

- **J.A. Gubner**, **L.L. Scharf**, and E.K.P. Chong, “Optimization of Exponential Error Rates for a Suboptimum Fusion Rule in Wireless Sensor Networks,” 45th Asilomar Conf on Sign, Syst, Computers, Pacific Grove, CA, Nov 6-9, 2011.

6 Interactions/Transitions

Participations and presentations at conferences and workshops are indicated in bold letters in the previous section. No transitions to report.

7 New Discoveries, Inventions, or Patent Disclosures

The many new discoveries from this program are reviewed in the section on Accomplishments/New Findings. There have been no inventions for which patents have been disclosed or filed.

8 Honors/Awards

Yuan Wang has received three prestigious awards during her PhD studies at Colorado State University: Madison Memorial Award for outstanding graduate student in Statistics, 2012; Remmenga Scholarship for excellence in applied statistics and statistical consulting, 2010; Graybill Award for excellence in linear models, 2010. She successfully defended her dissertation, Linear System Design for Fusion and Compression, on Aug 13, 2013. Her work was supported by AFOSR.

Louis Scharf is Life Fellow of IEEE and Recipient of several awards from IEEE. Edwin Chong is Fellow of IEEE and recipient of several awards from IEEE.

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[1] D. Ramirez, J. Via, I. Santamaria, and L.L. Scharf, "Locally Most Powerful Invariant Tests for Correlation and Sphericity of Gaussian Vectors," IEEE Trans Inform Theory, vol. 59, no. 4, pp 2128-2141 (Apr 2013).

[2] D. Ramirez, J. Iscar, J. Via, I. Santamaria, and L.L. Scharf, "The Locally Most Powerful Invariant Test for Detecting a Rank-P Gaussian Signal in White Noise," IEEE Workshop on Sensor Array and Multichannel (SAM) Signal Processing, 2012.

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[4] D. Ramirez, J. Via, I. Santamaria, and L.L. Scharf, "Multi-Sensor Beamsteering based on the Asymptotic Likelihood for Colored Signals," IEEE Workshop on Statistical Signal Processing, Nice, July, 2011.

[5] D. Ramirez, J. Via, I. Santamaria, and L.L. Scharf, "Detection of Spatially-Correlated Gaussian Time Series," IEEE Trans Signal Processing, vol 58, no 10, pp 5006-5015, 2010.

[6] N. Klausner, M.R. Azimi-Sadjadi, L.L. Scharf, and D. Cochran, "Space-time Coherence and its Null Distribution," IEEE Conf on Acoustics, Speech, and Signal Processing (ICASSP), Vancouver, BC, May 2013.

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