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Statistical, Graphical, and Learning Methods for Sensing, Surveillance, and Navigation Systems

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13. ABSTRACT (Maximum 200 words)

This final report summarizes our accomplishments over the four years of support under this grant. The first of two interrelated research areas focuses on scalable, high-performance inference algorithms for graphical and hierarchical models, This has clear applications to sensor exploitation applications such as tracking and distributed network fusion, including the development of message-passing algorithms for location-aware networks in complex (possibly GPS-denied) and often communications-limited environments. Our second thrust focuses on discovering graphical models not only relating different sensor observables but also discovering and linking them to higher-level "hidden" variables capturing the common context that relates them. One motivation here is to enhance both lower-level sensor processing (e.g., for object recognition) and higher-level context discovery through these models. A second motivation is the discovery of complex, possibly coordinated dynamic behavior exploiting emerging methods of Bayesian nonparametric modeling.

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STATISTICAL, GRAPHICAL, AND LEARNING METHODS FOR SENSING, SURVEILLANCE AND NAVIGATION SYSTEMS

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I. Summary: Objectives and Status of Effort

In this report we summarize our accomplishments under Grant FA9550-12-1-0287. This project has two interrelated research areas. The first of these focuses on scalable, high-performance inference algorithms for graphical and hierarchical models. This has clear applications to sensor exploitation applications such as tracking and distributed network fusion, including the development of message-passing algorithms for location-aware networks in complex (possibly GPS-denied) and often communications-limited environments. Our second thrust focuses on discovering graphical models not only relating different sensor observables but also discovering and linking them to higher-level "hidden" variables capturing the common context that relates them. One motivation here is to enhance both lower-level sensor processing (e.g., for object recognition) and higher-level context discovery through these models. A second motivation is the discovery of complex, possibly coordinated dynamic behavior exploiting emerging methods of Bayesian nonparametric modeling. Our research blends methods from statistics and probabilistic modeling, signal and image processing, communications and information theory, optimization, mathematical physics, graphical models, and machine learning theory, yielding new approaches to challenging problems in sensing, surveillance, and navigation. These are areas of clear and direct relevance to Air Force and more broadly DoD missions, and some of our methods are already impacting AF- and DoD-sponsored programs with industry.

The principal investigator for this effort is Professor Alan S. Willsky and the Co-Principal Investigator is Professor Moe Z. Win. Professors Willsky and Win are assisted in the conduct of this research by several graduate research assistants as well as additional thesis students not requiring stipend or tuition support from this grant. In the next section we briefly describe our research efforts; in Section III we indicate the individuals involved in this effort; in Section IV we list the publications supported by this effort; and in Section V we discuss several other topics including honors received by researchers involved in this project and transitions of our research.

II. Accomplishments

In this section we briefly describe our research under this grant. We limit ourselves here to a succinct summary and refer to the publications listed at the end of this report for detailed developments.

2.1 Efficient and Scalable Sensor Fusion and Exploitation Algorithms Based on Graphical and Hierarchical Models

The overall objective of this portion of our research is the development of methods for identifying classes of stochastic models for phenomena that vary over space, time, and hierarchy and that possess structure which can be exploited to construct efficient and scalable algorithms for statistical inference.

One important problem in machine learning approaches to "big data" problems in signal processing is the development of computationally efficient and scalable algorithms for Markov Chain Markov Chain (MCMC) sampling and in particular the sampling of very high-dimensional Gaussian processes. In many cases these processes are specified in terms of so-called graphical models that capture the dependency structure among the variables in a Gaussian process. However, even if the resulting graphs are sparse sampling of these processes has been a challenge, except for graphs with particular structure (such as acyclic graphs or graphs with small feedback vertex sets (see discussion to follow)). We have succeeded in developing two very powerful approaches to overcoming this challenge for models on rich set of graphs. The first of these applies for graphs that have the property that removing a relatively small set of edges exposes a graph with tractable sampling structure. In this case, one can use a so-called low-rank *subgraph perturbation* to perform iterative sampling that provably converges to provide samples from the full graphical model. For any graph that has this structure – and this includes quite a rich set of graphs – there typically are many different choices of small sets of edges that can be removed to expose the desired structure, and by switching among these different sets (which means perturbing different subgraphs in each iteration) one can generally achieve even faster convergence. The second of our approaches provides only approximate samples of the model but does so in a manner that allows highly parallelizable algorithms – in essence by partitioning the graph into several components, performing parallel sampling within each component and, at a slower rate, updating the variables involved in edges that connect those components. This is, in essence, a mixture of Jacobi-like iterations with Gauss-Seidel iterations, and as such, under very mild conditions it produces the correct mean values for all variables. The approximations that occur involve the covariances among the variables (due to the lower rate of updating across the components), and we have characterized in detail that approximation, allowing one to see the tradeoff between speed and accuracy (where speed is sacrificed at the expense of accuracy if such cross-component updates occur more frequently, and the opposite occurs if updates occur less frequently).

A second important part of our research has involved a thorough exploitation of the structure of a particular class of Gaussian graphical models, namely those that have comparatively small *Feedback Vertex Sets (FVS's)*. An FVS is a set of nodes that, if eliminated leave a cycle free graph. For any graphical model with an identified FVS, exact computation of means and variances can be accomplished by first performing cycle-free computation on the cycle-free graph exposed by eliminating the FVS nodes, then computing means and covariances for the FVS nodes, followed by a second round of cycle-free computations to yield means and variances at the remaining nodes. Roughly speaking this is equivalent to Gaussian elimination of the variables in the cycle-free graph, followed by computations on the FVS, and then back-substitution to the variables in the cycle-free graph. For the first and third step of this process the computations can be performed in a completely parallelized manner, through *message-passing,* using so-called *Belief Propagation*, which converges in a finite number of steps corresponding to the diameter of the cycle-free graph, so that the potential computational bottleneck is solely in the computation on the FVS itself, where brute-force solution yields computations that are cubic in the cardinality of the FVS. Hence, this approach works well in yielding exact solutions if the size of the FVS is relatively small. If this is not the case, one can use an approximate solution, in which we form a *pseudo-FVS* – i.e., a set of nodes that when removed yield a graph that still has some cycles – together with performing so-called *Loopy Belief Propagation (LBP)* in the remaining graph. In this case LBP isn't always guaranteed to converge (and when it does converge does so asymptotically), but we have developed a very simple approach to choosing the nodes for the pseudo-FVS that guarantees convergence, and we have also characterized precisely what the approximation is that such an algorithm makes. In particular, the computation of the mean is correct for all variables, the variances are also correct for the pseudo-FVS nodes, and the approximation of the variances for the other nodes can be precisely characterized in terms of the so-called "weighted walks" that this algorithm misses. We have demonstrated the effectiveness of this algorithm (and its superior performance to other available techniques) on a number of different graphs.

One of the advantages of LBP applied to any graph is that the algorithm structure involves only *local* graph properties – i.e., the computations at each node involves only its immediate neighbors together with the weights on the edges that connect the node to its neighbors, so that the algorithm is completely distributed, where the only "protocol" information that is included in the "messages" passed between nodes is the identity of the node sending the message. The algorithm just described, however, appears to require much more global computation (both to determine what nodes to include in the (pseudo-) FVS and then to perform the computations among the variables in that set. We have now developed a completely distributed of our algorithm that simultaneously (a) chooses the nodes to include in the (pseudo-) FVS; (b) performs message-passing among nodes that have been confirmed as not being in the (pseudo-) FVS; and (c) decides on the fly, node-by-node, when a node in the (pseudo-) FVS should be "released" to allow it to join the message passing. This algorithm is completely distributed, albeit with some additional overhead, as each node must provide some additional protocol information (first to establish if it should "join" the pseudo-FVS and then its status as "active," i.e., involved in the message passing, or not yet active).

One important part of our work is the study for efficient fusion of sensory data and environmental information for network localization and navigation in harsh propagation environments. Conventional filtering techniques fail to provide satisfactory performance in many important nonlinear or non-Gaussian scenarios. In addition, there is a lack of a unified methodology for the design and analysis of different filtering techniques. To address these problems, we have proposed a new filtering methodology called belief condensation (BC) filtering. Moreover, we have developed BC-based techniques for representing the positional belief in cooperative navigation networks. Such a method can reduce the communication overhead of network cooperation. The simulation results validated that the proposed techniques can handle the nonlinear dynamics and non-Gaussian beliefs with an improved accuracy versus complexity tradeoffs than conventional techniques.

The BC filtering techniques are applied in the design of localization and navigation algorithms. We have developed a framework for context-aided inertial navigation and efficient algorithms for its implementation based on belief condensation. The results presented provide a principled methodology to merge information from inertial measurements and situational context through Bayesian inference over an augmented hidden Markovian model (HMM). In addition, the techniques developed enable efficient and accurate context modeling and data fusion through belief condensation. The results obtained through experimentation for the case study of pedestrian foot-mounted IMU show that the proposed techniques can outperform existing techniques while maintaining complexities that meet the real-time requirements. The theoretical framework and algorithmic techniques presented can enable the integration of contextual information in inertial navigation systems and hence improve localization accuracy and robustness.

Another important part of our work is the study for joint design of location inference and power control strategies. These two operations of network navigation interrelate with each other, thus motivating the design of joint inference and control algorithms. We first determine the confidence region for location inference based on Fisher information analysis, and develop robust power control strategies to minimize the position errors of the agents within the confidence region. In the centralized setting, we show that the power control strategy can be transformed semi-definite programs. In the distributed setting, we decompose the problem into a sequential two-phase problem to circumvent the difficulties due to the lack of global knowledge. We show that the power control strategy in both phases can be transformed into second-order cone programs. The computation complexity of the proposed algorithm is analyzed using the sparsity property of the resource allocation. Simulation results show that the proposed strategies significantly improve localization accuracy and robustness compared to the conventional strategies.

2.2 Discovery of Graphical and Hidden Hierarchical, Contextual, and Dynamic Relationships in Complex Sensor Data

The research described in this section deals with methods for discovering latent structure in complex sensor data, where that latent structure can take the form of hierarchical graphical models of different types. Our research has led to the following lines of inquiry and results:

As described in the preceding section, there are very powerful estimation/signal processing algorithms that can be employed for graphical models with Feedback Vertex Sets of moderate size. This leads naturally to the question of whether one can *learn* models with small FVS's from data or can approximate specified covariance structure of a large Gaussian process with a model that has a comparatively small FVS. For cycle-free graphs there is a very powerful algorithm, known as the *Chow-Liu* (*CL*) algorithm to determine either the maximum-likelihood estimate of a cycle-free model (including the structure of the cycle-free graph) or, equivalently, the cycle-free model that is closest in Kullback-Leibler (K-L) divergence to a specified covariance. We have developed a suite of algorithms that exploit the CL-algorithm to yield the structure of Gaussian graphical models with (small) FVS's. The simplest of these algorithms is one in which we pre-specify the set of nodes to include in an FVS. The next algorithm is one that can, in principle, determine the FVS nodes and the structure of the remaining (cycle-free) graph. This algorithm has potential combinatorial issues as one, in principle, needs to search over all subsets of nodes up to a specified cardinality. Instead we have implemented and tested a greedy algorithm that adds FVS nodes one at a time, choosing nodes that provide the best approximation one by one. In addition, we have developed an algorithm in which the FVS nodes are all *hidden* or *latent*, i.e., they are nodes (and associated variables) that are added to the overall process so that (a) *conditioned* on these nodes, the set of variables we wish to model have a graphical structure that is acyclic; while (b) the *marginal* distribution on that set of variables, i.e., when we marginalize out the latent variables in order to reduce the K-L divergence or the resulting model from the specified covariance. This is an iterative algorithm, which exploits the algorithms we have developed for the case of a known FVS, and which we have proved does, indeed decrease K-L divergence at each iteration. Left open at this point is analyzing if and when the algorithm actually converges to the optimum in terms of minimizing K-L divergence.

We have also developed new algorithms and rich sets of models involving Bayesian nonparametric methods. Such models, exploiting Dirichlet processes, allow model complexity to be inferred at the same time as learning the parameters of such models. This has been the subject of considerable effort in the machine learning community, and our major contributions have been in developing methods for learning models for *dynamic* phenomena. Our first step in this development was the develop methods for learning *Hidden Markov Models* (*HMM's)* for signals, where included in the learning process is inferring the number of states in the HMM as well as the transition behavior among these states and the distribution of signal values when the HMM is in each of those states. This has been extended to a model with an additional level of hierarchy in which each HMM state specifies a *dynamic* model (e.g., an autoregressive time series or state space model) whose output generates observed signal values. One of the significant limitation of these HMM-based models is that HMM's must have geometric holding times in each state, which is not the case for many phenomena of interest. Hence we have explored and developed approaches that replace HMM's with Hidden *Semi*-Markov Processes (*HSMM's*) – models in which the sequence of hidden discrete states is, indeed, Markov, but in which the holding time in each state can be distributed in a far richer – and much more realistic – way. One of the challenges with such models (with either HMM's or HSMM's) is computational. We have developed methods along two lines. The first of these involves Gibbs sampling. Here we have exploited two different ideas. One involves introducing a rich but easily parameterized class of holding time distributions, namely so-called *negative binomial* distributions, so that we can streamline considerably the sampling of this part of the model. The other is to do approximate parallel sampling with occasional coordination among the steps, rather than the strictly required ordering in which sampling of different elements of a model must be done in order to do true Gibbs sampling (indeed, this is the generalization of the approach to approximate parallel sampling of large Gaussian models described in the preceding section; in fact, it was this challenge with nonparametric model sampling that motivated the analysis of the Gaussian case). The second method that we developed for inference for these complex models is the development of so-called variational methods for updating of parameters of these models – these involve approximations analogous to mean-field but for the complex nonparametric models considered in this portion of our work. These methods have received a great deal of attention both from other academic researchers including those involved in animal behavior analysis and from those involved in applied programs for DoD and other governmental agencies (see Section V).

We have also performed extensive research on optimization-based methods for a variety of problems. These have involved convex and semi-definite relaxations of difficult optimization problems. Our work has included theoretical advances in terms of new algorithms as well as theoretical guarantees. We have also developed new algorithms for problems of estimation on complex objects, including and in fact motivated by problems of attitude estimation. In addition, we have returned to a problem that was originally motivated by multiresolution signal analysis – inspired by the emergence of wavelets as an important signal processing tool. In earlier work we had developed estimation algorithms for stochastic models that lived on multiresolution trees (which in turn provided the initial motivation for our work on graphical models more generally). We had also developed methods for learning models for such signals in which the variables at coarser resolutions than the actual signal or phenomenon were viewed as hidden variables. In particular, in our earliest work in this area we developed methods analogous to those used to estimate state space models for constructing variables at each of the hidden nodes (corresponding to coarser representations of the signal of interest) where the structure of the multi-resolution tree was fixed but the dimensions of the variables at the hidden nodes was unknown and needed to be learned (in our case using ideas from canonical correlations and predictive efficiency). In subsequent work we developed methods for the complement of this earlier work, in which we restricted each of the hidden variables to be of the same dimension (namely scalar) as the individual values of the observed signal, but where the structure of the hierarchical tree was to be learned. Most recently, we have taken on what appears to be, and indeed is, a very ill-posed problem, namely learning both the structure of the multi-resolution tree as well as the dimensions of the variables at every hidden node. By exploiting an optimization-based framework with ideas analogous to those used in sparse signal recovery we have developed a method to solve this problem. In the process, we have identified conditions under which exact recovery is guaranteed (if an exact multi-resolution model exists and we have precise covariance information). This condition essentially corresponds to excluding what we had previously called *internal* models in which the hidden variables were actually deterministic functionals of the observed signal. Given noisy data, that situation is a singular one, so that this restriction is of no practical consequence.

We have developed statistical techniques for localization in harsh propagation environments. Non-line-of-sight (NLOS) propagation, multipath effect, and multiuser interference significantly affect the localization accuracy. Many techniques have been proposed to address this problem; most of them focus on improving the accuracy of ranging estimation, e.g., NLOS identification and mitigation. We have taken one step further and introduced the concept of range likelihood (RL) of a set of range-related measurements. We show that such RLs, instead of range point estimate, encapsulate all the measurement information that is needed to perform Bayesian. Then, we present effective techniques to estimate RLs based on generative model estimation, i.e, density estimation. We have assessed the performance of our proposed approaches by using experimental data from an indoor measurement campaign with FCC-compliant ultra-wideband radios. The results show that the proposed approaches can significantly improve the performance of wireless localization in harsh propagation environments.

We have derived the performance bounds for orthogonal frequency-division multiplexing (OFDM) ranging based on Fisher information analysis. In particular, we have decomposed the Fisher information matrix (FIM) for parameter estimation of multipath channels into the sum of those FIMs for different subcarriers. Based on the equivalent Fisher information analysis, we analyzed the effects of signal and channel parameters on the OFDM ranging accuracy. Our results provide the quantitative relationship between the ranging accuracy and the central frequency, the subcarrier spacing, the number of subcarriers, and the power allocation across the subcarriers. These results can serve as guidelines for designing OFDM ranging systems.

We have studied the spatiotemporal information coupling effects in cooperative network navigation. In cooperative navigation networks, the correlation of the inferred nodes' positions leads to the concept of *information coupling*. It hinders the development of distributed techniques that account for such correlation since the monitoring of neighbors' interaction requires difficult network coordination. We have developed a framework to characterize such effects using Fisher information analysis. In particular, we have derived the information coupling term in the equivalent Fisher information matrix (EFIM) for individual positional states and characterized the effective information obtained from each neighbor. Our results in this area show that the effect of information coupling sharply decreases with the network hopping distance. This local nature of information coupling can be exploited by cooperative techniques since the information coupling induced by distant neighbors' interactions can be safely ignored. The results will serve as guidelines for the design of efficient and accurate techniques for network navigation.

We have also studied resource allocation in network localization based on the computational geometry framework. To achieve the best localization performance, we have developed a computational geometry framework for optimal resource allocation in WNL. We first determine an affine map that transforms each resource allocation strategy into a point in 3-D Euclidian space. By exploiting geometric properties of these image points, we prove the sparsity property of the optimal resource allocation vector, i.e., the optimal localization performance can be achieved by allocating resources to only a small subset of neighboring nodes. Moreover, these geometric properties enable the reduction of the search space for optimal solutions. This allows us to design efficient resource allocation strategies. Numerical results show that the proposed strategies can achieve significant improvements in both localization performance and computation efficiency.

III. Personnel

The following is a list of individuals who have worked on research supported in whole or in part by the Air Force Office of Scientific Research under Grant FA9550-12-1-0287:

Prof. Alan S. Willsky, Edwin Sibley Webster Professor of Electrical Engineering, MIT
Prof. Moe Z. Win, Department of Aeronautics and Astronautics, MIT
Mr. Ying Liu, graduate student (Ph.D. completed)
Mr. Matthew Johnson, graduate student (Ph.D. completed)
Mr. James Saunderson, graduate student (Ph.D. completed)
Mr. Yuan Shen, graduate student (Ph.D. completed)
Mr. Tianheng Wang, graduate student (Ph.D. in progress)
Mr. Wenhan Dai, graduate student (Ph.D. in progress)

IV. Publications

The publications listed below represent papers, reports, and theses supported in whole or in part by the Air Force Office of Scientific Research under Grant FA9550-12-1-0287:

[1] V. Chandrasekaran, P.A. Parrilo, and A.S. Willsky, "Latent Variable Graphical Model Selection via Convex Optimization," *Annals of Statistics*, Vol. 40, No. 4, Aug. 2012, pp. 1935-1967 (with special designation as a "discussion paper).

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[40] J. Saunderson, "Semidefinite representations with Applications in Estimation and Inference," Ph.D. thesis, May 2015.

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V. RECOGNITION/INTERACTIONS/TRANSITIONS

In this section we summarize our and plans for transitions associated with research supported by AFOSR Grant FA9550-12-1-0287, as well as listing some important honors received by members of our research team.

Honors and Recognition

1) Prof. Willsky's student, Myungjin Choi, received a Sprowls Best Computer Science Thesis award from MIT's Department of Electrical Engineering and Computer Science.
2) Prof. Willsky's student, Venkat Chandrasekaran, received a Jin Au Kong Best Electrical Engineering Thesis award from MIT's Department of Electrical Engineering and Computer Science.
3) Prof. Willsky was selected as the 2013 William Gould Dow Distinguished Lecturer at the Dept. of EECS, University of Michigan. Prof. Willsky gave his Dow lecture in January 2013.
4) Prof. Willsky was selected as the 2013 Dean Lytle Electrical Engineering Endowed Lecturer at the University of Washington. Prof. Willsky gave his Lytle lectures in May 2013.
5) Prof. Win together with his students Yuan Shen, Wesley M. Gifford, and postdoctoral fellow Santiago Mazuelas received the IEEE Communications Society Fred W. Ellersick Prize, 2012.
6) Prof. Win and his student Wesley M. Gifford received the IEEE Communications Society Stephen O. Rice Prize in the Field of Communications Theory, 2012.
7) Prof. Win together with his postdoctoral fellow Alberto Rabbachin received IEEE Communications Society William R. Bennett Prize in the Field of Communications Networking, 2012.
8) Prof. Win received Institute of Advanced Study Natural Sciences and Technology Fellowship to give an invited lecture at the Institute of Advanced Study, University of Bologna, Bologna, Italy, in July 2012.
9) Prof. Win together with his students Henghui Lu and postdoctoral associate Santiago Mazuelas received a Best Paper Award at the IEEE International Conference on Communications in June 2013.
10) Prof. Win was named as recipient of the 2013 International Prize for Communications Cristoforo Colombo, established by the city of Genova in 1954.
11) Prof. Willsky was named as recipient of the 2014 SPS Society Award, the highest award bestowed by the IEEE Signal Processing Society.
12) Prof. Win was named as recipient of the 2014 Technical Recognition Award of the IEEE ComSoc Signal Processing and Communications Electronics (SPCE) Technical Committee.
13) Prof. Win together with his student Wenhan Dai and postdoctoral fellow Stefania Bartoletti received a Student Paper Award (first place) at the IEEE Canadian Workshop on Information Theory in July 2015.
14) A 2-day symposium in Prof. Willsky's honor was held at MIT on March 18-19, 2016.

Participation/Presentation at Meetings

In addition to the invited and contributed papers presented at various meetings, we also make note of the following:

1) Prof. Willsky gave a plenary lecture at the IFAC System Identification Conference in Brussels, Belgium in July 2012.
2) Prof. Win gave a presentation on "Network localization and navigation (a strategic advantage in modern warfare)," to U.S. Navy Naval Undersea Warfare Center (NUWC), Naval Sea Systems Command (NAVSEA) through the MIT Industrial Liaison Program Seminar, Cambridge, MA, October 2012.
3) Prof. Willsky was the 2013 William Gould Dow Distinguished Lecturer, the most prestigious invited lecture in the Dept. of EECS, University of Michigan.
4) Prof. Willsky was the 2013 Dean Lytle Electrical Engineering Endowed Lecturer, the most prestigious invited lecture in the Dept. of EE, University of Washington.
5) Prof. Win gave a keynote address at the IEEE International Conference on Wireless Communications and Signal Processing, in Hangzhou, China, in October 2013.
6) Prof. Win gave an Invited University Lecture at the 100th Anniversary Event of the Chulalongkorn University in Bangkok, Thailand, in June 2013.
7) Prof. Win gave a keynote address at the IEEE International Conference on Communications, Workshop on Advances in Network Localization and Navigation (ANLN) in Budapest, Hungary, in June 2013.
8) Prof. Win gave a keynote address at the International Symposium on Medical Information and Communication Technology (ISMICT), Florence, Italy, in April 2014.
9) Prof. Win gave a tutorial on "Network localization and navigation: from theory to practice" at the IEEE Wireless Communications and Networking Conference in New Orleans, LA, in March 2015.
10) Prof. Win gave a keynote address at the International Conference on Localization and GNSS in Gothenburg, Sweden, in June 2015.
11) Prof. Win gave a keynote address at the IEEE Canadian Workshop on Information Theory in St. John's, NL, Canada, in July 2015.
12) Prof. Win gave a plenary presentation at the IEEE International Conference on Communications in China in Shenzhen, in November 2015.

Consultative and Advisory Functions

We continue to be actively engaged in a number of activities relevant to the research being performed under our AFOSR grant:

(1) Prof. Willsky has acted as a consultant to Parietal Systems (PSI), and continues to consult with Systems and Technology Research (STR) on a number of research projects including ones that represent direct transitions of the technology being developed under our AFOSR Grant.
(2) In his role as a consultant to STR, Prof. Willsky served as one of the organizers and leader of the panel discussion at the AFRL-sponsored Workshop on Multi-INT Fusion for

Contested Environments, held in Dayton, OH in August 2014 (STR Contact: Dr. Mark Luettgen (mark.luettgen@stresearch.com); AFRL Contacts: Mr. Phillip Hanselman (phillip.hanselman@us.af.mil), Mr. Edmund Zelnio (edmund.zelnio@us.af.mil), and Dr. Juan Vasquez (juan.vasquez@us.af.mil).

Transitions

The following represent some of the transitions of our work.

1) Our methods for nonparametric learning and graphical models are being adapted and applied at STR to problems in multi-object tracking and multi-INT fusion under a program sponsored by AFRL Dayton. The STR contacts are Dr. Mark Luettgen (mark.luettgen@stresearch.com) and Dr. Stefano Coraluppi (stefano.coraluppi@stresearch.com).
2) Professor Willsky is consulting with Dr. Jeffrey Byrne (jeffrey.byrne@stresearch.com) on exploiting efficient methods of large-scale inference for Gaussian graphical models (one of the major components of our AFOSR program) for problems of visual object recognition under a DARPA program.
3) Our new methods for dynamic nonparametric models employing hierarchical Dirichlet processes are being used at STR for the characterization of motion behavior patterns under several programs. The STR points of contact are Dr. Peter Jones (peter.jones@stresearch.com) and Dr. Kirill Trapeznikov (kirill.trapeznikov@stresearch.com).
4) Prof. Willsky has worked with engineers at PSI on transition of message-passing algorithms for multi-object tracking, and our methods for nonparametric learning of dynamic behavior was utilized in several AF programs (now completed) at PSI. The PSI point of contact is Dr. John Fox (john.fox@parietal-systems.com).

1.

1. Report Type

Final Report

Primary Contact E-mail
Contact email if there is a problem with the report.

willsky@mit.edu

Primary Contact Phone Number
Contact phone number if there is a problem with the report

617-253-2356

Organization / Institution name

Lab. for Information and Decision Systems, MIT

Grant/Contract Title
The full title of the funded effort.

Statistical, Graphical, and Learning Methods for Fusion and Exploitation in Sensing and Navigation Systems

Grant/Contract Number
AFOSR assigned control number. It must begin with "FA9550" or "F49620" or "FA2386".

FA9550-12-1-0287

Principal Investigator Name
The full name of the principal investigator on the grant or contract.

Alan S. Willsky

Program Manager
The AFOSR Program Manager currently assigned to the award

Dr. Arje Nachman

Reporting Period Start Date

06/01/2012

Reporting Period End Date

05/31/2016

Abstract

This final report summarizes our accomplishments over the four years of support under this grant. The first of two interrelated research areas focuses on scalable, high-performance inference algorithms for graphical and hierarchical models, This has clear applications to sensor exploitation applications such as tracking and distributed network fusion, including the development of message-passing algorithms for location-aware networks in complex (possibly GPS-denied) and often communications-limited environments. Our second thrust focuses on discovering graphical models not only relating different sensor observables but also discovering and linking them to higher-level "hidden" variables capturing the common context that relates them. One motivation here is to enhance both lower-level sensor processing (e.g., for object recognition) and higher-level context discovery through these models. A second motivation is the discovery of complex, possibly coordinated dynamic behavior exploiting emerging methods of Bayesian nonparametric modeling.

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Archival Publications (published) during reporting period:

[1] V. Chandrasekaran, P.A. Parrilo, and A.S. Willsky, "Latent Variable Graphical Model Selection via Convex Optimization," Annals of Statistics, Vol. 40, No. 4, Aug. 2012, pp. 1935-1967 (with special designation as a "discussion paper).

[2] Y. Liu, V. Chandrasekaran, A. Anandkumar, and A.S. Willsky, "Feedback Message Passing for Inference in Gaussian Graphical Models," IEEE Trans. on Signal Processing, Vol. 60, No. 8, Aug. 2012.

[3] A. Anandkumar, V.Y.F. Tan, and A.S. Willsky, "High-Dimensional Robust Structure Learning of Ising Models on Sparse Random Graphs," Annals of Statistics. Vol. 40, No. 3, Jun. 2012, pp. 1346-1375.

[4] V. Chandrasekaran, B. Recht, P. Parrilo, and A.S. Willsky. "The Convex Geometry of Linear Inverse Problems," Foundations of Computational Mathematics, Vol. 12, No. 6, Dec. 2012.

[5] V. Chandrasekaran, P. Parrilo, and A.S. Willsky. "Convex Graph Invariants," SIAM Review, Vol. 54, No. 3, Sept. 2012.

[6] A. Anandkumar, V.Y.F. Tan, and A.S. Willsky, "High-Dimensional Gaussian Graphical Model Selection: Walk-Summability and Local Separation Criterion," J. of Machine Learning Research, Vol. 13, Aug. 2012, pp. 2293-2337.

[7] Y. Liu, O. Kosut, and A.S. Willsky, "Sampling GMRFs by Subgraph Correction," NIPS Workshop on Perturbation, Optimization, and Statistics, 2012.

[8] J.Saunderson, P.A. Parrilo, and A.S. Willsky, "Diagonal and Low-Rank Decompositions and Fitting Ellipsoids to Random Points," IEEE Conf. on Decision and Control, Dec. 2013.

[9] Y. Liu, O. Kosut, and A.S. Willsky, "Sampling from Gaussian Graphical Models Using Subgraph Perturbation," IEEE Int'l Symp. on Information Theory, July 2013.

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[27] Y. Liu, "Distributed Inference in Graphical Models and Learning Models with Small Feedback Vertex Sets," Ph.D. thesis, May 2014.
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[29] Y. Shen, W. Dai, and M. Z. Win, "Power Optimization for Network Localization," IEEE/ACM Trans. on Networking, vol. 22, no. 4, Aug. 2014, pp. 1337-1350.
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[39] Y. Liu and A.S. Willsky, "Learning Gaussian Graphical Models with Small Feedback Vertex Sets," in preparation.
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[41] W. Dai, Y. Shen, and M. Z. Win, "Resource Allocation for Network Localization: A Computational Geometry Framework," submitted.
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[43] J. Saunderson, P.A. Parrilo, and A.S. Willsky, "An Optimization-Based Approach to Learning Multi-Resolution Model Structure," in preparation.

2. New discoveries, inventions, or patent disclosures:

Do you have any discoveries, inventions, or patent disclosures to report for this period?

No

Please describe and include any notable dates

Do you plan to pursue a claim for personal or organizational intellectual property?

Changes in research objectives (if any):

NONE

Change in AFOSR Program Manager, if any:

Original PM: Dr. Jon Sjogren
Second PM: Dr. Tristan Nguyen
Current PM: Dr. Arje Nachman

Extensions granted or milestones slipped, if any:

AFOSR LRIR Number

LRIR Title

Reporting Period

Laboratory Task Manager

Program Officer

Research Objectives

Technical Summary

Funding Summary by Cost Category (by FY, $K)

	Starting FY	FY+1	FY+2
Salary			
Equipment/Facilities			
Supplies			
Total			

Report Document

Report Document - Text Analysis

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Appendix Documents

2. Thank You

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