

Shrinkage Algorithms for MMSE Covariance Estimation

Yilun Chen, *Student Member, IEEE*, Ami Wiesel, *Member, IEEE*, Yonina C. Eldar, *Senior Member, IEEE*, and Alfred O. Hero, *Fellow, IEEE*

Abstract—We address covariance estimation in the sense of minimum mean-squared error (MMSE) when the samples are Gaussian distributed. Specifically, we consider shrinkage methods which are suitable for high dimensional problems with a small number of samples (large p small n). First, we improve on the Ledoit-Wolf (LW) method by conditioning on a sufficient statistic. By the Rao-Blackwell theorem, this yields a new estimator called RBLW, whose mean-squared error dominates that of LW for Gaussian variables. Second, to further reduce the estimation error, we propose an iterative approach which approximates the clairvoyant shrinkage estimator. Convergence of this iterative method is established and a closed form expression for the limit is determined, which is referred to as the oracle approximating shrinkage (OAS) estimator. Both RBLW and OAS estimators have simple expressions and are easily implemented. Although the two methods are developed from different perspectives, their structure is identical up to specified constants. The RBLW estimator provably dominates the LW method for Gaussian samples. Numerical simulations demonstrate that the OAS approach can perform even better than RBLW, especially when n is much less than p . We also demonstrate the performance of these techniques in the context of adaptive beamforming.

Index Terms—Beamforming, covariance estimation, minimum mean-squared error (MMSE), shrinkage.

I. INTRODUCTION

COVARIANCE matrix estimation is a fundamental problem in signal processing and related fields. Many applications varying from array processing [12] to functional genomics [17] rely on accurately estimated covariance matrices. In recent years, estimation of high dimensional $p \times p$ covariance matrices under small sample size n has attracted considerable interest. Examples include classification on gene expression from microarray data [17], financial forecasting [7], [33], spectroscopic imaging [34], brain activation mapping

Manuscript received July 27, 2009; accepted May 12, 2010. Date of publication: June 14, 2010; date of current version September 15, 2010. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Hideaki Sakai. This work was supported in part by the AFOSR grant FA9550-06-1-0324 and NSF grant CCF 0830490. The work of A. Wiesel was supported by a Marie Curie Outgoing International Fellowship within the 7th European Community Framework Programme.

Y. Chen and A. O. Hero are with the Department of Electrical Engineering and Computer Science, University of Michigan, Ann Arbor, MI 48109 USA (e-mail: yilun@umich.edu; hero@umich.edu).

A. Wiesel is with the The Rachel and Selim Benin School of Computer Science and Engineering, Hebrew University of Jerusalem, 91904 Jerusalem, Israel (e-mail: ami.wiesel@huji.ac.il).

Y. C. Eldar is with the Technion—Israel Institute of Technology, Haifa, Israel 32000 (e-mail: yonina@ee.technion.ac.il).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TSP.2010.2053029

from fMRI [35] and many others. Standard estimation methods perform poorly in these large p small n settings. This is the main motivation for this paper.

The sample covariance is a common estimate for the unknown covariance matrix. When it is invertible, the sample covariance coincides with the classical maximum likelihood estimate. However, while it is an unbiased estimator, it does not minimize the mean-squared error (MSE). Indeed, Stein demonstrated that superior performance may be obtained by shrinking the sample covariance [2], [3]. Since then, many shrinkage estimators have been proposed under different performance measures. For example, Haff [4] introduced an estimator inspired by the empirical Bayes approach. Dey and Srinivasan [5] derived a minimax estimator under Stein's entropy loss function. Yang and Berger [6] obtained expressions for Bayesian estimators under a class of priors for the covariance. These works addressed the case of invertible sample covariance when $n \geq p$. Recently, Ledoit and Wolf (LW) proposed a shrinkage estimator for the case $n < p$ which asymptotically minimizes the MSE [8]. The LW estimator is well conditioned for small sample sizes and can thus be applied to high dimensional problems. In contrast to previous approaches, they show that performance advantages are distribution-free and not restricted to Gaussian assumptions.

In this paper, we show that the LW estimator can be significantly improved when the samples are in fact Gaussian. Specifically, we develop two new estimation techniques that result from different considerations. The first follows from the Rao-Blackwell theorem, while the second is an application of the ideas of [11] to covariance estimation.

We begin by providing a closed form expression for the optimal clairvoyant shrinkage estimator under an MSE loss criteria. This estimator is an explicit function of the unknown covariance matrix that can be used as an oracle performance bound. Our first estimator is obtained by applying the well-known Rao-Blackwell theorem [31] to the LW method, and is therefore denoted by RBLW. Using several nontrivial Haar integral computations, we obtain a simple closed form solution which provably dominates the LW method in terms of MSE. We then introduce an iterative shrinkage estimator which tries to approximate the oracle. This approach follows the methodology developed in [11] for the case of linear regression. Beginning with an initial naive choice, each iteration is defined as the oracle solution when the unknown covariance is replaced by its estimate obtained in the previous iteration. Remarkably, a closed form expression can be determined for the limit of these iterations. We refer to the limit as the oracle approximating shrinkage (OAS) estimator.

The OAS and RBLW solutions have similar structure that is related to a sphericity test as discussed in [18]–[20]. Both

OAS and RBLW estimators are intuitive, easy to compute and perform well with finite sample size. The RBLW technique provably dominates LW. Numerical results demonstrate that for small sample sizes, the OAS estimator is superior to both the RBLW and the LW methods.

To illustrate the proposed covariance estimators we apply them to problems of time series analysis and array signal processing. Specifically, in the context of time series analysis we establish performance advantages of OAS and RBLW to LW for covariance estimation in autoregressive models and in fractional Brownian motion models, respectively. In the context of beamforming, we show that RBLW and OAS can be used to significantly improve the Capon beamformer. In [12], a multitude of covariance matrix estimators were implemented in Capon beamformers, and the authors reported that the LW approach substantially improves performance as compared to other methods. We show here that even better performance can be achieved by using the techniques introduced in this paper.

Finally, we would like to point out that the performance gain achieved in the proposed estimators is only guaranteed when the samples are approximately Gaussian distributed. Although this is a common assumption in signal processing, when the sample distribution is far from Gaussian the proposed estimators may not perform as well as the LW estimator. We illustrate the performance gap for a heavy tailed multivariate Student-T distribution.

The paper is organized as follows. Section II formulates the problem. Section III introduces the oracle estimator together with the RBLW and OAS methods. Section IV represents numerical simulation results and applications in adaptive beamforming. Section V summarizes our principal conclusions. The proofs of theorems and lemmas are provided in the Appendix.

Notation: In the following, we depict vectors in lowercase boldface letters and matrices in uppercase boldface letters. $(\cdot)^T$ and $(\cdot)^H$ denote the transpose and the conjugate transpose, respectively. $\text{Tr}(\cdot)$, $\|\cdot\|_F$, and $\det(\cdot)$ are the trace, the Frobenius norm, and the determinant of a matrix, respectively. Finally, $\mathbf{A} \prec \mathbf{B}$ means that the matrix $\mathbf{B} - \mathbf{A}$ is positive definite, and $\mathbf{A} \succ \mathbf{B}$ means that the matrix $\mathbf{A} - \mathbf{B}$ is positive definite.

II. PROBLEM FORMULATION

Let $\{\mathbf{x}_i\}_{i=1}^n$ be a sample of independent identical distributed (i.i.d.) p -dimensional Gaussian vectors with zero mean and covariance $\mathbf{\Sigma}$. We do not assume $n \geq p$. Our goal is to find an estimator $\hat{\mathbf{\Sigma}}(\{\mathbf{x}_i\}_{i=1}^n)$ which minimizes the MSE

$$E \left\{ \left\| \hat{\mathbf{\Sigma}}(\{\mathbf{x}_i\}_{i=1}^n) - \mathbf{\Sigma} \right\|_F^2 \right\}. \quad (1)$$

It is difficult to compute the MSE of $\hat{\mathbf{\Sigma}}(\{\mathbf{x}_i\}_{i=1}^n)$ without additional constraints and, therefore, we restrict ourselves to a specific class of estimators that employ shrinkage [1], [7]. The unstructured classical estimator of $\mathbf{\Sigma}$ is the sample covariance $\hat{\mathbf{S}}$ defined as

$$\hat{\mathbf{S}} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T. \quad (2)$$

This estimator is unbiased $E\{\hat{\mathbf{S}}\} = \mathbf{\Sigma}$, and is also the maximum likelihood solution if $n \geq p$. However, it does not necessarily achieve low MSE due to its high variance and is usually ill-conditioned for large p problems. On the other hand, we may consider a naive but most well-conditioned estimate for $\mathbf{\Sigma}$

$$\hat{\mathbf{F}} = \frac{\text{Tr}(\hat{\mathbf{S}})}{p} \mathbf{I}. \quad (3)$$

This ‘‘structured’’ estimate will result in reduced variance with the expense of increasing the bias. A reasonable tradeoff between low bias and low variance is achieved by shrinkage of $\hat{\mathbf{S}}$ towards $\hat{\mathbf{F}}$, resulting in the following class of estimators:

$$\hat{\mathbf{\Sigma}} = (1 - \hat{\rho})\hat{\mathbf{S}} + \hat{\rho}\hat{\mathbf{F}}. \quad (4)$$

The estimator $\hat{\mathbf{\Sigma}}$ is characterized by the shrinkage coefficient $\hat{\rho}$, which is a parameter between 0 and 1 and can be a function of the observations $\{\mathbf{x}_i\}_{i=1}^n$. The matrix $\hat{\mathbf{F}}$ is referred to as the shrinkage target.¹

Throughout the paper, we restrict our attention to shrinkage estimates of the form (4). Our goal is to find a shrinkage coefficient $\hat{\rho}$ that minimizes the MSE (1). As we show in the next section, the optimal $\hat{\rho}$ minimizing the MSE depends in general on the unknown $\mathbf{\Sigma}$ and, therefore, in general cannot be implemented. Instead, we propose two different approaches to approximate the optimal shrinkage coefficient.

III. SHRINKAGE ALGORITHMS

A. The Oracle Estimator

We begin by deriving a clairvoyant oracle estimator that uses an optimal nonrandom coefficient to minimize the mean-squared error. In the following subsections we will show how to approximate the oracle using implementable data-driven methods.

The oracle estimate $\hat{\mathbf{\Sigma}}_O$ is the solution to

$$\begin{aligned} \min_{\rho} \quad & E \left\{ \left\| \hat{\mathbf{\Sigma}}_O - \mathbf{\Sigma} \right\|_F^2 \right\} \\ \text{s.t.} \quad & \hat{\mathbf{\Sigma}}_O = (1 - \rho)\hat{\mathbf{S}} + \rho\hat{\mathbf{F}}. \end{aligned} \quad (5)$$

The optimal parameter ρ_O is provided in the following theorem.

Theorem 1: Let $\hat{\mathbf{S}}$ be the sample covariance of a set of p -dimensional vectors $\{\mathbf{x}_i\}_{i=1}^n$. If $\{\mathbf{x}_i\}_{i=1}^n$ are i.i.d. Gaussian vectors with covariance $\mathbf{\Sigma}$, then the solution to (5) is

$$\begin{aligned} \rho_O &= \frac{E\{\text{Tr}((\mathbf{\Sigma} - \hat{\mathbf{S}})(\hat{\mathbf{F}} - \hat{\mathbf{S}}))\}}{E\{\|\hat{\mathbf{S}} - \hat{\mathbf{F}}\|_F^2\}} \\ &= \frac{\left(1 - \frac{2}{p}\right) \text{Tr}(\mathbf{\Sigma}^2) + \text{Tr}^2(\mathbf{\Sigma})}{\left(n + 1 - \frac{2}{p}\right) \text{Tr}(\mathbf{\Sigma}^2) + \left(1 - \frac{n}{p}\right) \text{Tr}^2(\mathbf{\Sigma})}. \end{aligned} \quad (6)$$

Proof: Equation (6) was established in [7] for any distribution of $\{\mathbf{x}_i\}_{i=1}^n$. Under the additional Gaussian assumption

¹The convex combination in (4) can be generalized to the linear combination of $\hat{\mathbf{S}}$ and $\hat{\mathbf{F}}$. The reader is referred to [13] for further discussion.

tion, (7) can be obtained from straightforward evaluation of the expectations

$$E\{\text{Tr}((\mathbf{\Sigma} - \hat{\mathbf{S}})(\hat{\mathbf{F}} - \hat{\mathbf{S}}))\} = \frac{\text{Tr}(\mathbf{\Sigma})}{p} E\{\text{Tr}(\hat{\mathbf{S}})\} \\ - \frac{E\{\text{Tr}^2(\hat{\mathbf{S}})\}}{p} - E\{\text{Tr}(\mathbf{\Sigma}\hat{\mathbf{S}})\} + E\{\text{Tr}(\hat{\mathbf{S}}^2)\} \quad (8)$$

and

$$E\left\{\|\hat{\mathbf{S}} - \hat{\mathbf{F}}\|_F^2\right\} = E\{\text{Tr}(\hat{\mathbf{S}}^2)\} \\ - 2E\{\text{Tr}(\hat{\mathbf{S}}\hat{\mathbf{F}})\} + E\{\text{Tr}(\hat{\mathbf{F}}^2)\} \\ = E\{\text{Tr}(\hat{\mathbf{S}}^2)\} - \frac{E\{\text{Tr}^2(\hat{\mathbf{S}})\}}{p}. \quad (9)$$

Equation (7) is a result of using the following identities [27]:

$$E\{\text{Tr}(\hat{\mathbf{S}})\} = \text{Tr}(\mathbf{\Sigma}), \quad (10)$$

$$E\{\text{Tr}(\hat{\mathbf{S}}^2)\} = \frac{n+1}{n} \text{Tr}(\mathbf{\Sigma}^2) + \frac{1}{n} \text{Tr}^2(\mathbf{\Sigma}) \quad (11)$$

and

$$E\{\text{Tr}^2(\hat{\mathbf{S}})\} = \text{Tr}^2(\mathbf{\Sigma}) + \frac{2}{n} \text{Tr}(\mathbf{\Sigma}^2). \quad (12)$$

Note that (6) specifies the optimal shrinkage coefficient for any sample distribution while (7) only holds for the Gaussian distribution. It can be shown that (7) will be a close approximation to (6) when the sample distribution is close to the Gaussian distribution in variational norm.

B. The Rao-Blackwell Ledoit-Wolf (RBLW) Estimator

The oracle estimator defined by (5) is optimal but cannot be implemented, since the solution specified by both (6) and (7) depends on the unknown $\mathbf{\Sigma}$. Without any knowledge of the sample distribution, LW [7], [8] proposed to approximate the oracle using the following consistent estimate of (6):

$$\hat{\rho}_{LW} = \frac{\sum_{i=1}^n \left\| \mathbf{x}_i \mathbf{x}_i^T - \hat{\mathbf{S}} \right\|_F^2}{n^2 \left[\text{Tr}(\hat{\mathbf{S}}^2) - \frac{\text{Tr}^2(\hat{\mathbf{S}})}{p} \right]}. \quad (13)$$

They then proved that when both $n, p \rightarrow \infty$ and $p/n \rightarrow c$, $0 < c < \infty$, (13) converges to (6) in probability regardless of the sample distribution. The LW estimator $\hat{\mathbf{\Sigma}}_{LW}$ is then defined by plugging $\hat{\rho}_{LW}$ into (4). In [8] LW also showed that the optimal ρ_O (6) is always between 0 and 1. To further improve the performance, they suggested using a modified shrinkage parameter

$$\hat{\rho}_{LW}^* = \min(\hat{\rho}_{LW}, 1) \quad (14)$$

instead of $\hat{\rho}_{LW}$.

The Rao-Blackwell LW (RBLW) estimator described below provably improves on the LW method under the Gaussian model. The motivation for the RBLW originates from the fact that under the Gaussian assumption on $\{\mathbf{x}_i\}_{i=1}^n$, a sufficient statistic for estimating $\mathbf{\Sigma}$ is the sample covariance $\hat{\mathbf{S}}$. Intuitively, the LW estimator is a function of not only $\hat{\mathbf{S}}$ but other statistics

and therefore, by the Rao-Blackwell theorem, can be improved. Specifically, the Rao-Blackwell theorem [31] states that if $g(X)$ is an estimator of a parameter θ , then the conditional expectation of $g(X)$ given $T(X)$, where T is a sufficient statistic, is never worse than the original estimator $g(X)$ under any convex loss criterion. Applying the Rao-Blackwell theorem to the LW estimator yields the following result.

Theorem 2: Let $\{\mathbf{x}_i\}_{i=1}^n$ be independent p -dimensional Gaussian vectors with covariance $\mathbf{\Sigma}$, and let $\hat{\mathbf{S}}$ be the sample covariance of $\{\mathbf{x}_i\}_{i=1}^n$. The conditioned expectation of the LW covariance estimator is

$$\hat{\mathbf{\Sigma}}_{RBLW} = E[\hat{\mathbf{\Sigma}}_{LW} | \hat{\mathbf{S}}] \quad (15)$$

$$= (1 - \hat{\rho}_{RBLW}) \hat{\mathbf{S}} + \hat{\rho}_{RBLW} \hat{\mathbf{F}} \quad (16)$$

where

$$\hat{\rho}_{RBLW} = \frac{\binom{n-2}{n} \cdot \text{Tr}(\hat{\mathbf{S}}^2) + \text{Tr}^2(\hat{\mathbf{S}})}{(n+2) \left[\text{Tr}(\hat{\mathbf{S}}^2) - \frac{\text{Tr}^2(\hat{\mathbf{S}})}{p} \right]}. \quad (17)$$

This estimator satisfies

$$E\left\{\|\hat{\mathbf{\Sigma}}_{RBLW} - \mathbf{\Sigma}\|_F^2\right\} \leq E\left\{\|\hat{\mathbf{\Sigma}}_{LW} - \mathbf{\Sigma}\|_F^2\right\} \quad (18)$$

for every $\mathbf{\Sigma}$.

The proof of Theorem 2 is given in the Appendix.

Similarly to the LW estimator, we propose the modification

$$\hat{\rho}_{RBLW}^* = \min(\hat{\rho}_{RBLW}, 1) \quad (19)$$

instead of $\hat{\rho}_{RBLW}$.

C. The OAS Estimator

The basic idea of the LW estimator is to asymptotically approximate the oracle, which is designed for large sample size. For a large number of samples the LW asymptotically achieves the minimum MSE with respect to shrinkage estimators. Clearly, the RBLW also inherits this property. However, for very small n , which is often the case of interest, there is no guarantee that such optimality still holds. To illustrate this point, consider the extreme example when only one sample is available. For $n = 1$ we have both $\hat{\rho}_{LW}^* = 1$ and $\hat{\rho}_{RBLW}^* = 1$, which indicates that $\hat{\mathbf{\Sigma}}_{LW} = \hat{\mathbf{\Sigma}}_{RBLW} = \hat{\mathbf{S}}$. This, however, contradicts our expectations since if a single sample is available, it is more reasonable to expect more confidence to be put on the more parsimonious $\hat{\mathbf{F}}$ rather than $\hat{\mathbf{S}}$.

In this section, we aim at developing a new estimation method which can approximate the oracle for finite n . Rather than employing asymptotic solutions we consider an alternative approach based on [11]. In (7), we obtained a closed-form formula of the oracle estimator under Gaussian assumptions. The idea behind the OAS is to approximate this oracle via an iterative procedure. We initialize the iterations with an initial guess of $\mathbf{\Sigma}$ and iteratively refine it. The initial guess $\hat{\mathbf{\Sigma}}_0$ might be the sample covariance, the RBLW estimate or any other symmetric nonnegative definite estimator. We replace $\mathbf{\Sigma}$ in the oracle solution by $\hat{\mathbf{\Sigma}}_0$ yielding $\hat{\mathbf{\Sigma}}_1$, which in turn generates $\hat{\mathbf{\Sigma}}_2$ through our proposed iteration. The iteration process is

continued until convergence. The limit, denoted as $\hat{\Sigma}_{\text{OAS}}$, is the OAS solution. Specifically, the proposed iteration is

$$\hat{\rho}_{j+1} = \frac{\left(\frac{1-2}{p}\right) \text{Tr}(\hat{\Sigma}_j \hat{\mathbf{S}}) + \text{Tr}^2(\hat{\Sigma}_j)}{\left(\frac{n+1-2}{p}\right) \text{Tr}(\hat{\Sigma}_j \hat{\mathbf{S}}) + \left(\frac{1-n}{p}\right) \text{Tr}^2(\hat{\Sigma}_j)} \quad (20)$$

$$\hat{\Sigma}_{j+1} = (1 - \hat{\rho}_{j+1}) \hat{\mathbf{S}} + \hat{\rho}_{j+1} \hat{\mathbf{F}}. \quad (21)$$

Comparing to (7), notice that in (20) $\text{Tr}(\Sigma)$ and $\text{Tr}(\Sigma^2)$ are replaced by $\text{Tr}(\hat{\Sigma}_j)$ and $\text{Tr}(\hat{\Sigma}_j \hat{\mathbf{S}})$, respectively. Here $\text{Tr}(\hat{\Sigma}_j \hat{\mathbf{S}})$ is used instead of $\text{Tr}(\hat{\Sigma}_j^2)$ since the latter would always force $\hat{\rho}_j$ to converge to 1 while the former leads to a more meaningful limiting value.

Theorem 3: For any initial guess $\hat{\rho}_0$ that is between 0 and 1, the iterations specified by (20), (21) converge as $j \rightarrow \infty$ to the following estimate:

$$\hat{\Sigma}_{\text{OAS}} = (1 - \hat{\rho}_{\text{OAS}}^*) \hat{\mathbf{S}} + \hat{\rho}_{\text{OAS}}^* \hat{\mathbf{F}} \quad (22)$$

where

$$\hat{\rho}_{\text{OAS}}^* = \min \left(\frac{\left(\frac{1-2}{p}\right) \text{Tr}(\hat{\mathbf{S}}^2) + \text{Tr}^2(\hat{\mathbf{S}})}{\left(\frac{n+1-2}{p}\right) \left[\text{Tr}(\hat{\mathbf{S}}^2) - \frac{\text{Tr}^2(\hat{\mathbf{S}})}{p} \right]}, 1 \right). \quad (23)$$

In addition, $0 < \hat{\rho}_{\text{OAS}}^* \leq 1$.

Proof: Plugging in $\hat{\Sigma}_j$ from (21) into (20) and simplifying yields

$$\hat{\rho}_{j+1} = \frac{1 - \left(\frac{1-2}{p}\right) \hat{\phi} \hat{\rho}_j}{1 + n \hat{\phi} - \left(\frac{n+1-2}{p}\right) \hat{\phi} \hat{\rho}_j} \quad (24)$$

where

$$\hat{\phi} = \frac{\text{Tr}(\hat{\mathbf{S}}^2) - \frac{\text{Tr}^2(\hat{\mathbf{S}})}{p}}{\text{Tr}(\hat{\mathbf{S}}^2) + \left(\frac{1-2}{p}\right) \text{Tr}^2(\hat{\mathbf{S}})}. \quad (25)$$

Since $\text{Tr}(\hat{\mathbf{S}}^2) \geq \text{Tr}^2(\hat{\mathbf{S}})/p$, $0 \leq \hat{\phi} < 1$.

Next we introduce a new variable

$$\hat{b}_j = \frac{1}{1 - \left(\frac{n+1-2}{p}\right) \hat{\phi} \hat{\rho}_j}. \quad (26)$$

Then

$$\hat{\rho}_j = \frac{1 - \hat{b}_j^{-1}}{\left(\frac{n+1-2}{p}\right) \hat{\phi}}. \quad (27)$$

Substituting (27) to (24), after simplification we obtain that

$$1 - \hat{b}_{j+1}^{-1} = \frac{n \hat{\phi} + \left(\frac{1-2}{p}\right) \hat{\phi} \hat{b}_j^{-1}}{n \hat{\phi} + \hat{b}_j^{-1}} \quad (28)$$

which leads to the following geometric series:

$$\hat{b}_{j+1} = \frac{n \hat{\phi}}{1 - \left(\frac{1-2}{p}\right) \hat{\phi}} \hat{b}_j + \frac{1}{1 - \left(\frac{1-2}{p}\right) \hat{\phi}}. \quad (29)$$

It is easy to see that

$$\lim_{j \rightarrow \infty} \hat{b}_j = \begin{cases} \infty, & \text{if } \frac{n \hat{\phi}}{1 - \left(\frac{1-2}{p}\right) \hat{\phi}} \geq 1 \\ \frac{1}{1 - \left(\frac{n+1-2}{p}\right) \hat{\phi}}, & \text{if } \frac{n \hat{\phi}}{1 - \left(\frac{1-2}{p}\right) \hat{\phi}} < 1 \end{cases}. \quad (30)$$

Therefore $\hat{\rho}_j$ also converges as $j \rightarrow \infty$ and $\hat{\rho}_{\text{OAS}}^*$ is given by

$$\hat{\rho}_{\text{OAS}}^* = \lim_{j \rightarrow \infty} \hat{\rho}_j = \begin{cases} \frac{1}{\left(\frac{n+1-2}{p}\right) \hat{\phi}} & \text{if } \left(\frac{n+1-2}{p}\right) \hat{\phi} > 1 \\ 1, & \text{if } \left(\frac{n+1-2}{p}\right) \hat{\phi} \leq 1 \end{cases}. \quad (31)$$

We can write (31) equivalently as

$$\hat{\rho}_{\text{OAS}}^* = \min \left(\frac{1}{\left(\frac{n+1-2}{p}\right) \hat{\phi}}, 1 \right). \quad (32)$$

Equation (23) is obtained by substituting (25) into (31).

Note that (31) $\hat{\rho}_{\text{OAS}}^*$ is naturally bounded within $[0, 1]$. This is different from $\hat{\rho}_{\text{LW}}^*$ and $\hat{\rho}_{\text{RBLW}}^*$, where the $[0, 1]$ constraint is imposed in an *ad hoc* fashion. We also note that the iterative procedure described in (20) and (21) is only used to establish the limiting closed form OAS solution. In practice, the OAS estimate is calculated using (22) and (23), so that iterations are unnecessary.

D. Shrinkage and Sphericity Statistics

We now turn to theoretical comparisons with RBLW and OAS. The only difference is in their shrinkage coefficients. Although derived from distinct approaches, it is easy to see that $\hat{\rho}_{\text{OAS}}^*$ shares the same structure as $\hat{\rho}_{\text{RBLW}}^*$. In fact, they can both be expressed as the parameterized function

$$\hat{\rho}_E^* = \min \left(\alpha + \frac{\beta}{\hat{U}}, 1 \right) \quad (33)$$

with \hat{U} defined as

$$\hat{U} = \frac{1}{p-1} \left(\frac{p \cdot \text{Tr}(\hat{\mathbf{S}}^2)}{\text{Tr}^2(\hat{\mathbf{S}})} - 1 \right). \quad (34)$$

For $\hat{\rho}_E^* = \hat{\rho}_{\text{OAS}}^*$, α and β of (33) are given by

$$\begin{aligned} \alpha &= \alpha_{\text{OAS}} = \frac{1}{n+1-\frac{2}{p}} \\ \beta &= \beta_{\text{OAS}} = \frac{p+1}{\left(\frac{n+1-2}{p}\right)(p-1)} \end{aligned} \quad (35)$$

while for $\hat{\rho}_E^* = \hat{\rho}_{\text{RBLW}}^*$

$$\begin{aligned} \alpha &= \alpha_{\text{RBLW}} = \frac{n-2}{n(n+2)} \\ \beta &= \beta_{\text{RBLW}} = \frac{(p+1)n-2}{n(n+2)(p-1)}. \end{aligned} \quad (36)$$

Thus the only difference between $\hat{\rho}_{\text{OAS}}^*$ and $\hat{\rho}_{\text{RBLW}}^*$ is the choice of α and β . The statistic \hat{U} arises in tests of sphericity of Σ [19], [20], i.e., testing whether or not Σ is a scaled identity matrix. In particular, \hat{U} is the locally most powerful invariant test statistic for sphericity under orthogonal transformations [18].

The smaller the value of \hat{U} , the more likely that Σ is proportional to an identity matrix \mathbf{I} . Similarly, in our shrinkage algorithms, the smaller the value of \hat{U} , the more shrinkage occurs in $\hat{\Sigma}_{\text{OAS}}$ and $\hat{\Sigma}_{\text{RBLW}}$.

Under the following asymptotic conditions [8]:

$$n \rightarrow \infty, \quad p \rightarrow \infty, \quad \text{and} \quad \frac{p}{n} \rightarrow \text{constant} \quad (37)$$

OAS and RBLW are equivalent, since $\hat{\rho}_{\text{OAS}}^*$ and $\hat{\rho}_{\text{RBLW}}^*$ converge to each other. In [8] the authors have proved that the LW estimator is asymptotically optimal under condition (37). Note that RBLW dominates LW for Gaussian samples. Therefore, RBLW, OAS, and LW are asymptotically equivalent to each other when the samples are Gaussian.

It is also important to note that while RBLW and OAS share the same structure and are asymptotically equivalent, their finite sample performance may be entirely different, especially when n is small. For example, in the extreme case that only one sample is available, $\hat{\rho}_{\text{OAS}}^* = 1$ while $\hat{\rho}_{\text{RBLW}}^* = 0$, regardless of the value of the sample. This observation will be further explored in the numerical simulations later.

IV. NUMERICAL SIMULATIONS

In this section, we implement and test the proposed covariance estimators. We first compare the estimated MSE of the RBLW and OAS techniques with the LW method. We then consider their application to the problem of adaptive beamforming, and show that they lead to improved performance of Capon beamformers.

A. MSE Comparison

To test the MSE of the covariance estimators we designed two sets of experiments with different shapes of Σ . Such covariance matrices have been used to study covariance estimators in [10]. We use (14), (19), and (23) to calculate the shrinkage coefficients for the LW, the RBLW, and the OAS estimators. For comparison, the oracle estimator (5) uses the true Σ and is included as a benchmark lower bound on MSE for comparison. For all simulations, we set $p = 100$ and let n range from 6 to 30. Each simulation is repeated 5000 times and the MSE and shrinkage coefficients are plotted as a function of n . The 95% confidence intervals of the MSE and shrinkage coefficients were found to be smaller than the marker size and are omitted in the figures.

In the first experiment, an autoregressive covariance structured Σ is used. We let Σ be the covariance matrix of a Gaussian AR(1) process [32]

$$\Sigma_{ij} = r^{|i-j|} \quad (38)$$

where Σ_{ij} denotes the entry of Σ in row i and column j . We take $r = 0.1, 0.5$ and 0.9 for the different simulations reported here. Figs. 1(a)–3(a) show the MSE of the estimators for different values of r . Figs. 1(b)–3(b) show the corresponding shrinkage coefficients.

In Fig. 4, we plot the MSE of the first three iterations obtained by the iterative procedure in (21) and (20). For comparison, we also plot the results of the OAS and the oracle estimator. We set

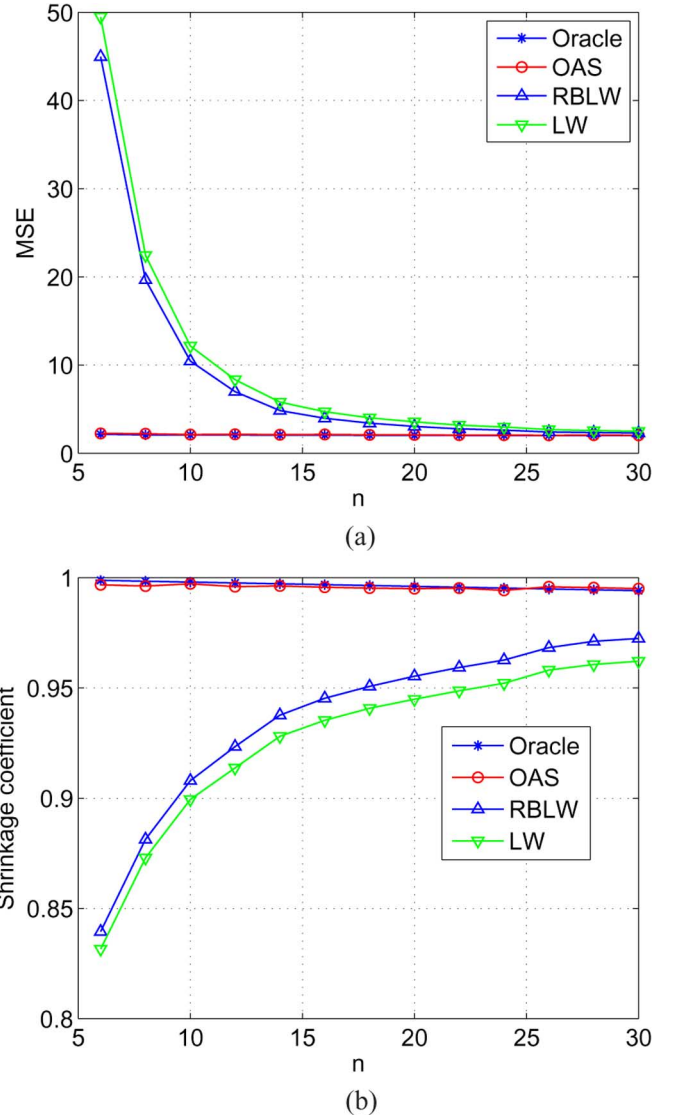


Fig. 1. AR(1) process: Comparison of covariance estimators when $p = 100$, $r = 0.1$.

$r = 0.5$ in this example and start the iterations with the initial guess $\hat{\Sigma}_0 = \hat{\mathbf{S}}$. From Fig. 4 it can be seen that as the iterations proceed, the MSE gradually decreases towards that of the OAS estimator, which is very close to that of the oracle.

In the second experiment, we set Σ as the covariance matrix associated with the increment process of fractional Brownian motion (FBM) exhibiting long-range dependence. Such processes are often used to model internet traffic [29] and other complex phenomena. The form of the covariance matrix is given by

$$\Sigma_{ij} = \frac{1}{2} [(|i-j|+1)^{2h} - 2|i-j|^{2h} + (|i-j|-1)^{2h}] \quad (39)$$

where $h \in [0.5, 1]$ is the so-called Hurst parameter. The typical value of h is below 0.9 in practical applications. We choose h equal to 0.6, 0.7, and 0.8. The MSE and shrinkage coefficients are plotted in Figs. 5(a)–7(a) and 5(b)–7(b), respectively.

From the simulation results in the above two experiments, it is evident that the OAS estimator performs very closely to the ideal

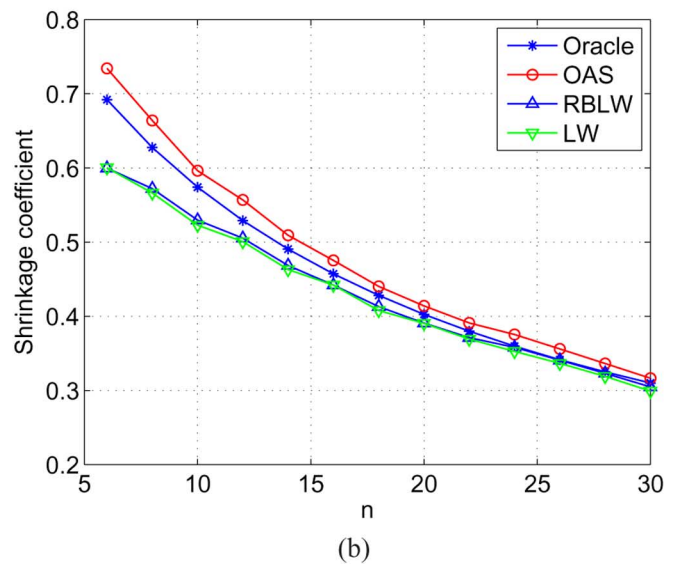
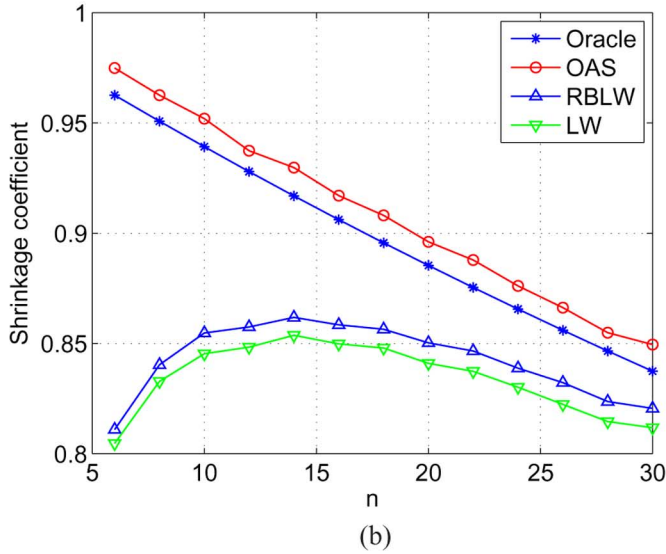
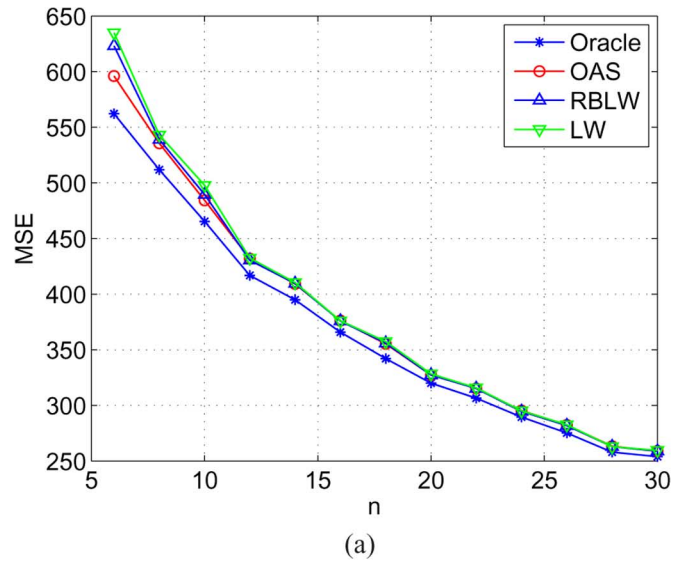
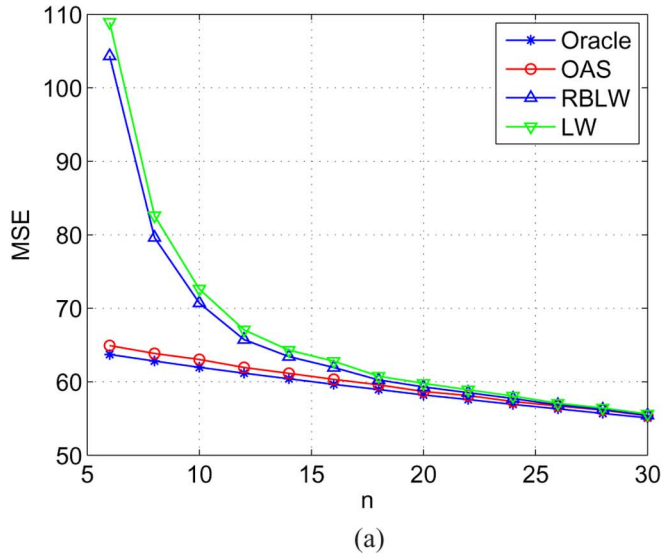


Fig. 2. AR(1) process: Comparison of covariance estimators when $p = 100$, $r = 0.5$.

Fig. 3. AR(1) process: Comparison of covariance estimators when $p = 100$, $r = 0.9$.

oracle estimator. When n is small, the OAS significantly outperforms the LW and the RBLW. The RBLW improves slightly upon the LW, but this is not obvious at the scale of the plots shown in the figures. As expected, all the estimators converge to a common value when n increases.

As indicated in (5) and shown from simulation results, the oracle shrinkage coefficient ρ_O decreases in the sample number n . This makes sense since $(1 - \rho_O)$ can be regarded as a measure of “confidence” assigned to $\hat{\Sigma}$. Intuitively, as more observations are available, one acquires higher confidence in the sample covariance $\hat{\Sigma}$ and therefore ρ_O decreases. This characteristic is exhibited by $\hat{\rho}_{OAS}^*$ but not by $\hat{\rho}_{RBLW}^*$ and $\hat{\rho}_{LW}^*$. This may partially explain why OAS outperforms RBLW and LW for small samples.

It can be shown that all the estimators perform better when the sphericity of Σ increases, corresponding to small values of r and h . Indeed, the eigenvalues of Σ are more dispersed as r and h increases. As the dispersion of the eigenvalues is inversely related to the sphericity, larger sphericity in Σ indicates that better performance can be obtained by shrinking the sample covariance towards identity.

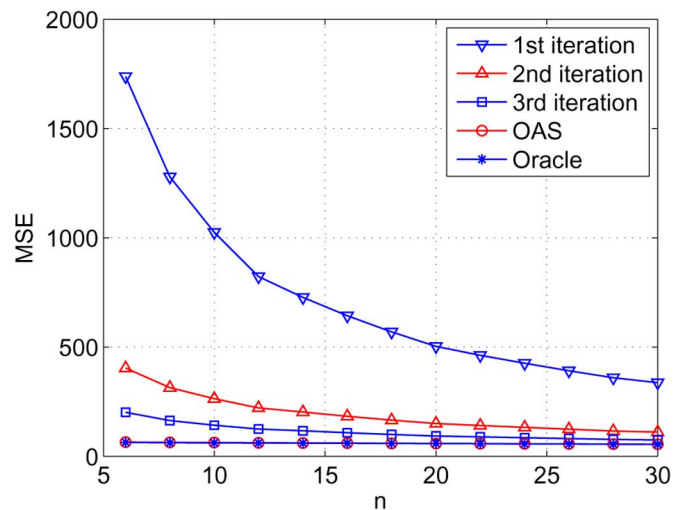


Fig. 4. AR(1) process: Comparison of MSE in different iterations, when $p = 100$, $r = 0.5$.

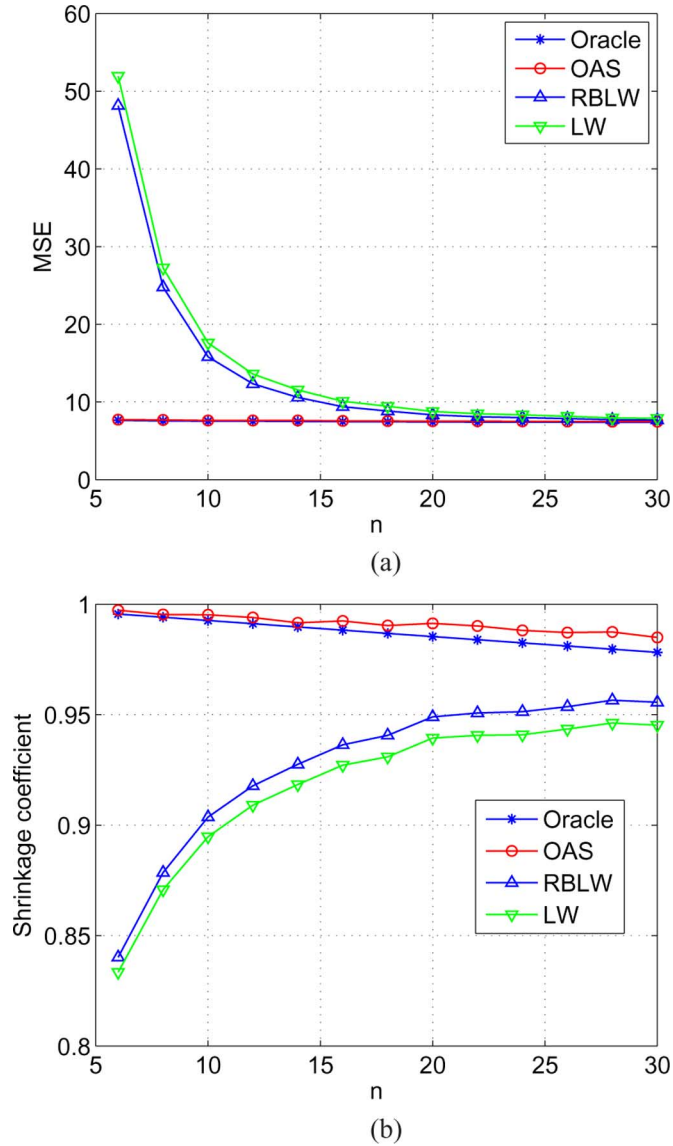


Fig. 5. Incremental FBM process: Comparison of covariance estimators when $p = 100, h = 0.6$.

Our experience through numerous simulations with arbitrary parameters suggests that in practice the OAS is preferable to the RBLW. However, as the RBLW is provably better than the LW there exists counter examples. For the incremental FBM covariance $\hat{\Sigma}$ in (39), we set $h = 0.9, n = 20, p = 100$. The simulation is repeated for 5000 times and the result is shown in Table I, where $\text{MSE}(\hat{\Sigma}_{\text{RBLW}}) < \text{MSE}(\hat{\Sigma}_{\text{OAS}}) < \text{MSE}(\hat{\Sigma}_{\text{LW}})$. The differences are very small but establish that the OAS estimator does not always dominate the RBLW. However, we suspect that this will only occur when Σ has a very small sphericity, a case of less interest in practice as small sphericity of Σ would suggest a different shrinkage target than $\hat{\mathbf{F}}$.

Finally, we would like to point out that there is no free lunch. The superiority of the RBLW and OAS methods over the LW is only guaranteed when the samples are truly Gaussian. When the Gaussian assumption does not hold, RBLW and OAS may perform worse than LW. We performed an experiment (data not shown) with a heavy tailed (multivariate Student-T) sample distribution that tends to produce outliers. We observed that the

TABLE I
INCREMENTAL FRM PROCESS: COMPARISON OF MSE AND SHRINKAGE COEFFICIENTS WHEN $h = 0.9, n = 20, p = 100$

	MSE	Shrinkage coefficient
Oracle	428.9972	0.2675
OAS	475.2691	0.3043
RBLW	472.8206	0.2856
LW	475.5840	0.2867

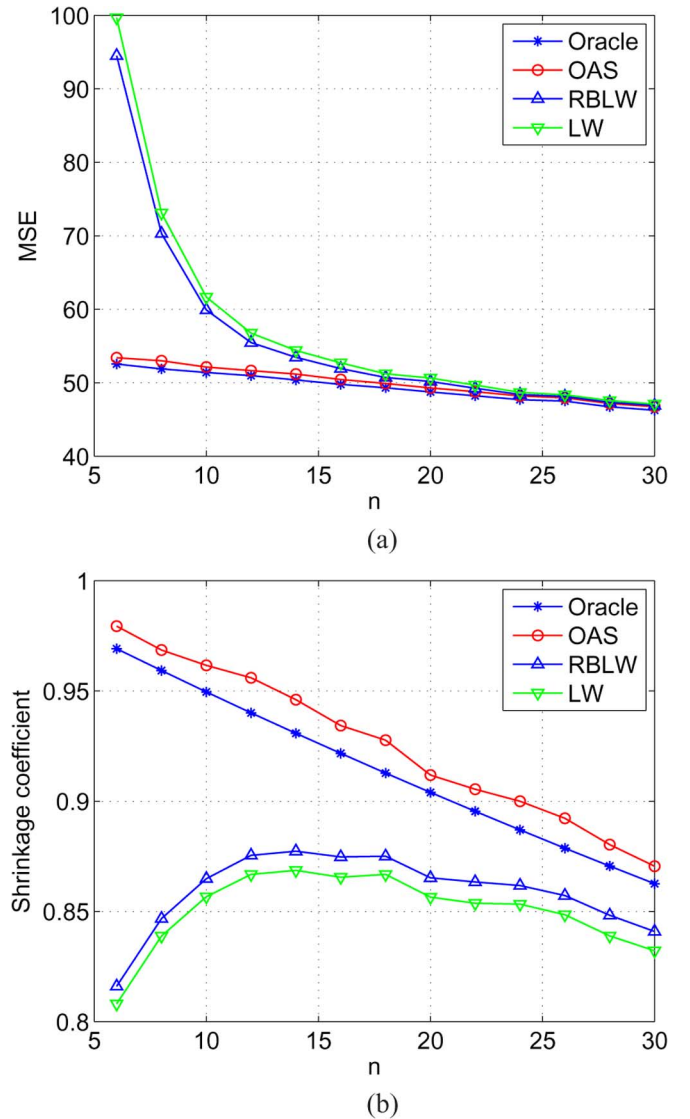


Fig. 6. Incremental FBM process: Comparison of covariance estimators when $p = 100, h = 0.7$.

RBLW no longer dominates the LW, due to outliers in the data, and the OAS outperforms the LW only when $n < 10$. Thus outlier resistant modifications of OAS and RBLW are a worthy topic of investigation.

B. Application to the Capon Beamformer

Next we applied the proposed shrinkage estimators to the signal processing problem of adaptive beamforming. Assume

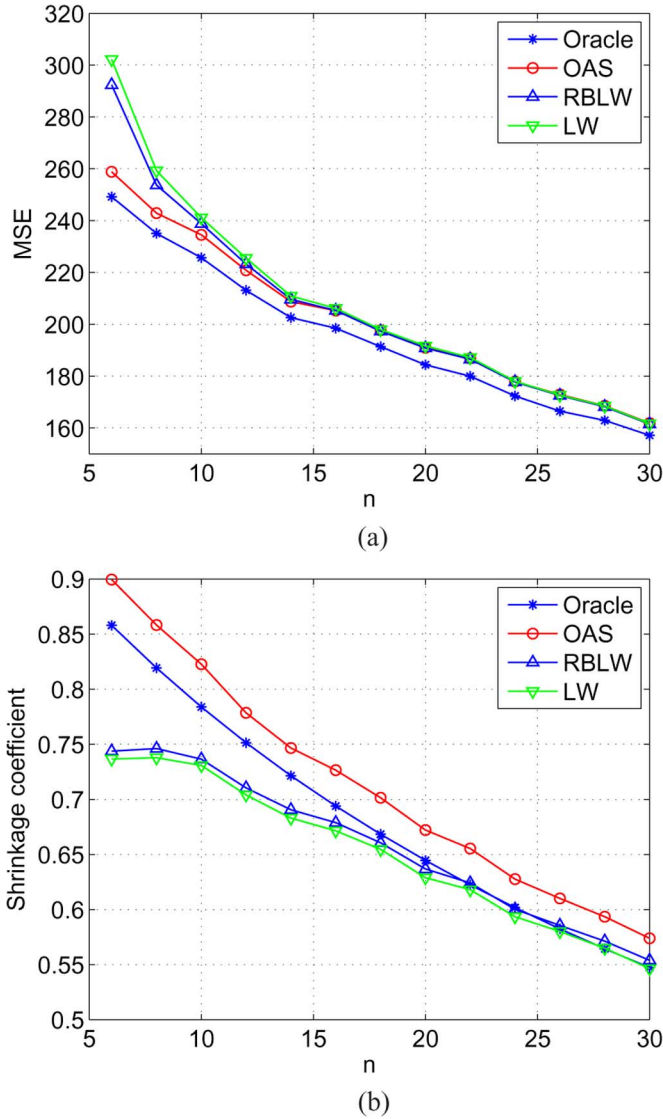


Fig. 7. Incremental FBM process: Comparison of covariance estimators when $p = 100, h = 0.8$.

that a narrowband signal of interest $s(t)$ impinges on an unperturbed uniform linear array (ULA) [30] comprised of p sensors. The complex valued vector of n snapshots of the array output is

$$\mathbf{x}(t) = \mathbf{a}(\theta_s)s(t) + \mathbf{n}(t), \quad \text{for } t = 1, \dots, n \quad (40)$$

where θ_s is parameter vector determining the location of the signal source and $\mathbf{a}(\theta)$ is the array response for a generic source location θ . Specifically

$$\mathbf{a}(\theta) = [1, e^{-j\omega}, e^{-j2\omega}, \dots, e^{-j(p-1)\omega}]^T \quad (41)$$

where ω is the spatial frequency. The noise/interference vector $\mathbf{n}(t)$ is assumed to be zero mean i.i.d. Gaussian distributed. We model the unknown $s(t)$ as a zero mean i.i.d. Gaussian process.

In order to recover the unknown $s(t)$ the Capon beamformer [30] linearly combines the array output $\mathbf{x}(t)$ using a vector of weights \mathbf{w} , calculated by

$$\mathbf{w} = \frac{\boldsymbol{\Sigma}^{-1}\mathbf{a}(\theta_s)}{\mathbf{a}(\theta_s)^H\boldsymbol{\Sigma}^{-1}\mathbf{a}(\theta_s)} \quad (42)$$

where $\boldsymbol{\Sigma}$ is the covariance of $\mathbf{x}(t)$. The covariance $\boldsymbol{\Sigma}$ is unknown while the array response $\mathbf{a}(\theta)$ and the source direction-of-arrival (DOA) θ_s are known. After obtaining the weight vector \mathbf{w} , the signal of interest $s(t)$ is estimated by $\mathbf{w}^H\mathbf{x}(t)$.

To implement (42) the matrix $\boldsymbol{\Sigma}$ needs to be estimated. In [12] it was shown that using the LW estimator could substantially improve Capon beamformer performance over conventional methods. As we will see below, the OAS and the RBLW shrinkage estimators can yield even better results.

Note that the signal and the noise processes are complex valued and $\boldsymbol{\Sigma}$ is thus a complex (Hermitian symmetric) covariance matrix. To apply the OAS and RBLW estimators we use the same approach as used in [12] to extend the real LW covariance estimator to the complex case. Given a $p \times 1$ complex random vector \mathbf{x} , we represent it as a $2p \times 1$ vector of its real and imaginary parts

$$\mathbf{x}_s = \begin{pmatrix} \text{Re}(\mathbf{x}) \\ \text{Im}(\mathbf{x}) \end{pmatrix}. \quad (43)$$

Then the estimate of the complex covariance can be represented as

$$\hat{\boldsymbol{\Sigma}}_s = \begin{pmatrix} \hat{\boldsymbol{\Sigma}}_{rr} & \hat{\boldsymbol{\Sigma}}_{ri} \\ \hat{\boldsymbol{\Sigma}}_{ir} & \hat{\boldsymbol{\Sigma}}_{ii} \end{pmatrix} \quad (44)$$

where $\hat{\boldsymbol{\Sigma}}_{rr}$, $\hat{\boldsymbol{\Sigma}}_{ri}$, $\hat{\boldsymbol{\Sigma}}_{ir}$ and $\hat{\boldsymbol{\Sigma}}_{ii}$ are $p \times p$ sub-matrices. The real representation (44) can be mapped to the full complex covariance matrix $\boldsymbol{\Sigma}$ as

$$\hat{\boldsymbol{\Sigma}} = (\hat{\boldsymbol{\Sigma}}_{rr} + \hat{\boldsymbol{\Sigma}}_{ii}) + j(\hat{\boldsymbol{\Sigma}}_{ir} - \hat{\boldsymbol{\Sigma}}_{ri}). \quad (45)$$

Using this representation we can easily extend the real valued LW, RBLW, and OAS estimators to complex scenarios. As pointed in [12], this approach does not preserve the circular property of $\hat{\boldsymbol{\Sigma}}_s$, i.e.

$$\begin{aligned} \hat{\boldsymbol{\Sigma}}_{rr} &= \hat{\boldsymbol{\Sigma}}_{ii} \\ \hat{\boldsymbol{\Sigma}}_{ri} &= -\hat{\boldsymbol{\Sigma}}_{ir}. \end{aligned} \quad (46)$$

We note that exploiting the circular property in $\hat{\boldsymbol{\Sigma}}_s$ would yield better estimators for complex covariance matrices. For purposes of this simple illustration we implement the simple methodology described above for a beamforming problem.

We conduct the beamforming simulation as follows. A ULA of $p = 10$ sensor elements with half wavelength spacing is assumed and three signals were simulated as impinging on the array. The signal of interest has a DOA $\theta_s = 20^\circ$ and a power $\sigma_s^2 = 10$ dB above the complex Gaussian sensor noise. The other two signals are mutually independent interferences. One is at DOA angle of $\theta_{i1} = -30^\circ$ and the other one is close to the source of interest with its angular location corresponding to a spatial frequency of

$$\omega_{i2} = \pi \sin(\theta_s) + 2\pi\frac{\gamma}{p}$$

where γ is set to 0.9. Each signal has power 15 dB above the sensor noise.

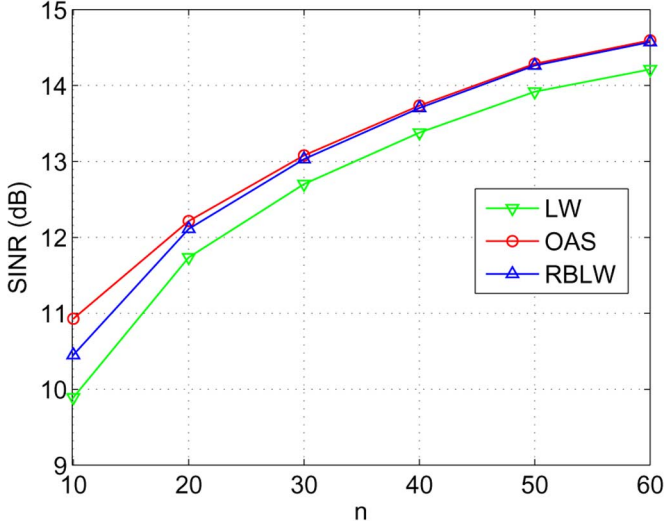


Fig. 8. Comparison between different covariance shrinkage estimators in the Capon beamformer. SINR is plotted versus number of snapshots n . OAS achieves as much as 1 dB improvement over the LW.

We implemented the complex versions of the LW, the RBLW and the OAS covariance estimators, described above, and used them in place of Σ in the Capon beamformer expression (42). The beamforming performance gain is measured by the SINR defined as [12]

$$\text{mean SINR} = \frac{1}{K} \sum_{k=1}^K \frac{\sigma_s^2 |\hat{\mathbf{w}}_k^H \mathbf{a}(\theta_s)|^2}{\hat{\mathbf{w}}_k^H [\Sigma - \sigma_s^2 \mathbf{a}(\theta_s) \mathbf{a}(\theta_s)^H] \hat{\mathbf{w}}_k} \quad (47)$$

where K is the number of Monte Carlo simulations and $\hat{\mathbf{w}}_k$ is the weight vector obtained by (42) in the k th simulation. Here $K = 5000$ and n varies from 10 to 60 in step of 5 snapshots. The gain is shown in Fig. 8. In [12] it was reported that the LW estimator achieves the best SINR performances among several contemporary Capon-type beamformers. It can be seen in Fig. 8 that the RBLW and the OAS do even better, improving upon the LW estimator. Note also that the greatest improvement for OAS in the small n regime is observed.

V. CONCLUSION

In this paper, we introduced two new shrinkage algorithms to estimate covariance matrices when the samples are Gaussian distributed. The RBLW estimator was shown to improve upon the state-of-the-art LW method by virtue of the Rao-Blackwell theorem. The OAS estimator was developed by iterating on the optimal oracle estimate, where the limiting form was determined analytically. The RBLW provably dominates the LW, and the OAS empirically outperforms both the RBLW and the LW in most experiments we have conducted. The proposed OAS and RBLW estimators have simple explicit expressions and are easy to implement. Furthermore, they share similar structure differing only in the form of the shrinkage coefficients. We applied these estimators to the Capon beamformer and obtained significant gains in performance as compared to the LW Capon beamformer implementation.

Throughout the paper we set the shrinkage target as the scaled identity matrix. The theory developed here can be extended to other nonidentity shrinkage targets. An interesting question for future research is how to choose appropriate targets in specific applications.

Another important future direction is to explore the outlier resistant modifications to the OAS and RBLW estimators presented here. We will investigate more robust shrinkage estimators in our future work.

APPENDIX

In this Appendix we prove Theorem 2. Theorem 2 is non-trivial and requires careful treatment using results from the theory of Haar measure and singular Wishart distributions. The proof will require several intermediate results stated as lemmas. We begin with a definition.

Definition 1: Let $\{\mathbf{x}_i\}_{i=1}^n$ be a sample of p -dimensional i.i.d. Gaussian vectors with mean zero and covariance Σ . Define a $p \times n$ matrix \mathbf{X} as

$$\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n). \quad (48)$$

Denote $r = \min(p, n)$ and define the singular value decomposition on \mathbf{X} as

$$\mathbf{X} = \mathbf{H}\mathbf{\Lambda}\mathbf{Q} \quad (49)$$

where \mathbf{H} is a $p \times r$ matrix such that $\mathbf{H}^T \mathbf{H} = \mathbf{I}$, $\mathbf{\Lambda}$ is a $r \times r$ diagonal matrix in probability 1, comprised of the singular values of \mathbf{X} , and \mathbf{Q} is a $r \times n$ matrix such that $\mathbf{Q}\mathbf{Q}^T = \mathbf{I}$.

Next we state and prove three lemmas.

Lemma 1: Let $(\mathbf{H}, \mathbf{\Lambda}, \mathbf{Q})$ be matrices defined in Definition 1. Then \mathbf{Q} is independent of \mathbf{H} and $\mathbf{\Lambda}$.

Proof: For the case $n \leq p$, \mathbf{H} is a $p \times n$ matrix, $\mathbf{\Lambda}$ is a $n \times n$ square diagonal matrix and \mathbf{Q} is a $n \times n$ orthogonal matrix. The pdf of \mathbf{X} is

$$p(\mathbf{X}) = \frac{1}{(2\pi)^{pn/2} \det(\Sigma)^{n/2}} e^{-1/2 \text{Tr}(\mathbf{X}\mathbf{X}^T \Sigma^{-1})}. \quad (50)$$

Since $\mathbf{X}\mathbf{X}^T = \mathbf{H}\mathbf{\Lambda}\mathbf{\Lambda}^T \mathbf{H}^T$, the joint pdf of $(\mathbf{H}, \mathbf{\Lambda}, \mathbf{Q})$ is

$$p(\mathbf{H}, \mathbf{\Lambda}, \mathbf{Q}) = \frac{1}{(2\pi)^{pn/2} \det(\Sigma)^{n/2}} e^{-1/2 \text{Tr}(\mathbf{H}\mathbf{\Lambda}\mathbf{\Lambda}^T \mathbf{H}^T \Sigma^{-1})} \times J(\mathbf{X} \rightarrow \mathbf{H}, \mathbf{\Lambda}, \mathbf{Q}) \quad (51)$$

where $J(\mathbf{X} \rightarrow \mathbf{H}, \mathbf{\Lambda}, \mathbf{Q})$ is the Jacobian converting from \mathbf{X} to $(\mathbf{H}, \mathbf{\Lambda}, \mathbf{Q})$. According to [21, Lemma 2.4]

$$J(\mathbf{X} \rightarrow \mathbf{H}, \mathbf{\Lambda}, \mathbf{Q}) = 2^{-n} \det(\mathbf{\Lambda})^{p-n} \prod_{j < k}^n (\lambda_j^2 - \lambda_k^2) g_{n,p} \times (\mathbf{H}) g_{n,n}(\mathbf{Q}) \quad (52)$$

where λ_j denotes the j th diagonal element of $\mathbf{\Lambda}$ and $g_{n,p}(\mathbf{H})$ and $g_{n,n}(\mathbf{Q})$ are functions of \mathbf{H} and \mathbf{Q} defined in [21].

Substituting (52) into (51), $p(\mathbf{H}, \mathbf{\Lambda}, \mathbf{Q})$ can be factorized into functions of $(\mathbf{H}, \mathbf{\Lambda})$ and \mathbf{Q} . Therefore, \mathbf{Q} is independent of \mathbf{H} and $\mathbf{\Lambda}$.

Similarly, one can show that \mathbf{Q} is independent of \mathbf{H} and \mathbf{A} when $n > p$. ■

Lemma 2: Let \mathbf{Q} be a matrix defined in Definition 1. Denote \mathbf{q} as an arbitrary column vector of \mathbf{Q} and q_j as the j th element of \mathbf{q} . Then

$$E \{q_j^4\} = \frac{3}{n(n+2)} \quad (53)$$

and

$$E \{q_k^2 q_j^2\} = \frac{1}{n(n+2)}, \quad k \neq j. \quad (54)$$

Proof: The proof is different for the cases that $n \leq p$ and $n > p$, which are treated separately.

(1) Case $n \leq p$:

In this case, \mathbf{Q} is a real Haar matrix and is isotropically distributed [22], [24], [25], i.e., for any orthogonal matrices Φ and Ψ which are independent with \mathbf{Q} , $\Phi\mathbf{Q}$ and $\mathbf{Q}\Psi$ have the same pdf of \mathbf{Q}

$$p(\Phi\mathbf{Q}) = p(\mathbf{Q}\Psi) = p(\mathbf{Q}). \quad (55)$$

Following [23] in the complex case, we now use (55) to calculate the fourth order moments of elements of \mathbf{Q} . Since \mathbf{Q} and

$$\begin{bmatrix} \cos \theta & \sin \theta & & & \\ -\sin \theta & \cos \theta & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 \end{bmatrix} \mathbf{Q}$$

are also identically distributed, we have

$$\begin{aligned} E \{Q_{11}^4\} &= E \{(\mathbf{Q}_{11} \cos \theta + \mathbf{Q}_{21} \sin \theta)^4\} \\ &= \cos^4 \theta E \{Q_{11}^4\} + \sin^4 \theta E \{Q_{21}^4\} \\ &\quad + 6 \cos^2 \theta \sin^2 \theta E \{Q_{11}^2 Q_{21}^2\} \\ &\quad + 2 \cos^3 \theta \sin \theta E \{Q_{11}^3 Q_{21}\} \\ &\quad + 2 \cos \theta \sin^3 \theta E \{Q_{11} Q_{21}^3\}. \end{aligned} \quad (56)$$

By taking $\theta = -\theta$ in (56), it is easy to see that

$$2 \cos^3 \theta \sin \theta E \{Q_{11}^3 Q_{21}\} + 2 \cos \theta \sin^3 \theta E \{Q_{11} Q_{21}^3\} = 0.$$

The elements of $[Q_{ii}]$ are identically distributed. We thus have $E \{Q_{11}^4\} = E \{Q_{21}^4\}$, and hence

$$E \{Q_{11}^4\} = (\cos^4 \theta + \sin^4 \theta) E \{Q_{11}^4\} + 6 \cos^2 \theta \sin^2 \theta E \{Q_{11}^2 Q_{21}^2\}. \quad (57)$$

By taking $\theta = \pi/3$

$$E \{Q_{11}^4\} = 3E \{Q_{11}^2 Q_{21}^2\}. \quad (58)$$

Now we consider $E \left\{ \left(\sum_{j=1}^n Q_{j1}^2 \right)^2 \right\}$. Since $\mathbf{Q}^T \mathbf{Q} = \mathbf{Q}\mathbf{Q}^T = \mathbf{I}$, $\sum_{j=1}^n Q_{j1}^2 = 1$. This implies

$$\begin{aligned} 1 &= \sum_{j=1}^n E \{Q_{j1}^4\} + \sum_{j \neq k} E \{Q_{j1}^2 Q_{k1}^2\} \\ &= nE \{Q_{11}^4\} + n(n-1)E \{Q_{11}^2 Q_{21}^2\}. \end{aligned} \quad (59)$$

Substituting (58) into (59), we obtain that

$$E \{Q_{11}^4\} = \frac{3}{n(n+2)} \quad (60)$$

and

$$E \{Q_{11}^2 Q_{21}^2\} = \frac{1}{n(n+2)}. \quad (61)$$

It is easy to see that $E \{q_j^4\} = E \{Q_{11}^4\}$ and $E \{q_j^2 q_k^2\} = E \{Q_{11}^2 Q_{21}^2\}$. Therefore (53) and (54) are proved for the case of $n \leq p$.

(2) Case $n > p$:

The pdf of \mathbf{q} can be obtained by [21, Lemma 2.2]

$$p(\mathbf{q}) = C_1 \det(\mathbf{I} - \mathbf{q}\mathbf{q}^T)^{(n-p-2)/2} I(\mathbf{q}\mathbf{q}^T \prec \mathbf{I}) \quad (62)$$

where

$$C_1 = \frac{\pi^{-p/2} \Gamma\left\{\frac{n}{2}\right\}}{\Gamma\left\{\frac{(n-p)}{2}\right\}} \quad (63)$$

and $I(\cdot)$ is the indicator function specifying the support of \mathbf{q} . Equation (62) indicates that the elements of \mathbf{q} are identically distributed. Therefore, $E \{q_j^4\} = E \{q_1^4\}$ and $E \{q_j^2 q_k^2\} = E \{q_1^2 q_2^2\}$. By the definition of expectation

$$E \{q_1^4\} = C_1 \int_{\mathbf{q}\mathbf{q}^T \prec \mathbf{I}} q_1^4 \det(\mathbf{I} - \mathbf{q}\mathbf{q}^T)^{(n-p-2)/2} d\mathbf{q} \quad (64)$$

and

$$E \{q_1^2 q_2^2\} = C_1 \int_{\mathbf{q}\mathbf{q}^T \prec \mathbf{I}} q_1^2 q_2^2 \det(\mathbf{I} - \mathbf{q}\mathbf{q}^T)^{(n-p-2)/2} d\mathbf{q}. \quad (65)$$

Noting that

$$\mathbf{q}\mathbf{q}^T \prec \mathbf{I} \Leftrightarrow \mathbf{q}^T \mathbf{q} < 1 \quad (66)$$

and

$$\det(\mathbf{I} - \mathbf{q}\mathbf{q}^T) = 1 - \mathbf{q}^T \mathbf{q} \quad (67)$$

we have

$$\begin{aligned} E \{q_1^4\} &= C_1 \int_{\mathbf{q}^T \mathbf{q} < 1} q_1^4 (1 - \mathbf{q}^T \mathbf{q})^{1/2(n-p-2)} d\mathbf{q} \\ &= C_1 \int_{\sum_{j=1}^p q_j^2 < 1} q_1^4 \left(1 - \sum_{j=1}^p q_j^2 \right)^{1/2(n-p-2)} \\ &\quad dq_1 \cdots dq_p. \end{aligned} \quad (68)$$

By changing variable of integration (q_1, q_2, \dots, q_p) to $(r, \theta_1, \theta_2, \dots, \theta_{p-1})$ such that

$$\begin{cases} q_1 = r \cos \theta_1 \\ q_2 = r \sin \theta_1 \cos \theta_2 \\ q_3 = r \sin \theta_1 \sin \theta_2 \cos \theta_3 \\ \vdots \\ q_{p-1} = r \sin \theta_1 \sin \theta_2 \cdots \sin \theta_{p-2} \cos \theta_{p-1} \\ q_p = r \sin \theta_1 \sin \theta_2 \cdots \sin \theta_{p-2} \sin \theta_{p-1} \end{cases} \quad (69)$$

we obtain

$$\begin{aligned} E \{q_1^4\} &= C_1 \int_0^\pi d\theta_1 \int_0^\pi d\theta_2 \cdots \\ &\int_0^\pi d\theta_{p-2} \int_0^{2\pi} d\theta_{p-1} \\ &\cdot \int_0^1 r^4 \cos^4 \theta_1 (1-r^2)^{1/2(n-p-2)} \\ &\cdot \left| \frac{\partial(q_1, \dots, q_p)}{\partial(r, \theta_1, \dots, \theta_{p-1})} \right| dr \end{aligned} \quad (70)$$

where

$$\left| \frac{\partial(q_1, \dots, q_p)}{\partial(r, \theta_1, \dots, \theta_{p-1})} \right| = r^{p-1} \sin^{p-2} \theta_1 \sin^{p-3} \theta_2 \cdots \sin \theta_{p-2}$$

is the Jacobian associated with the change of variable. Therefore

$$\begin{aligned} E \{q_1^4\} &= C_1 \cdot \int_0^\pi \cos^4 \theta_1 \sin^{p-2} \theta_1 d\theta_1 \cdot \int_0^\pi \sin^{p-3} \theta_2 d\theta_2 \\ &\cdot \int_0^\pi \sin^{p-4} \theta_3 d\theta_3 \cdots \int_0^\pi \sin \theta_{p-2} d\theta_{p-2} \\ &\cdot \int_0^{2\pi} d\theta_{p-1} \cdot \int_0^1 r^{p+3} (1-r^2)^{1/2(n-p-2)} dr \\ &= \frac{\pi^{-p/2} \Gamma\left\{\frac{n}{2}\right\}}{\Gamma\left\{\frac{(n-p)}{2}\right\}} \cdot \frac{3\pi^{1/2} \Gamma\left\{\frac{(p-1)}{2}\right\}}{4 \Gamma\left\{\frac{(p+4)}{2}\right\}} \\ &\cdot \pi^{1/2} \frac{\Gamma\left\{\frac{(p-2)}{2}\right\}}{\Gamma\left\{\frac{(p-1)}{2}\right\}} \cdot \pi^{1/2} \frac{\Gamma\left\{\frac{(p-3)}{2}\right\}}{\Gamma\left\{\frac{(p-2)}{2}\right\}} \\ &\cdots \pi^{1/2} \frac{\Gamma\left\{\frac{3}{2}\right\}}{\Gamma\left\{\frac{5}{2}\right\}} \cdot \pi^{1/2} \frac{\Gamma\{1\}}{\Gamma\left\{\frac{3}{2}\right\}} \cdot 2\pi \\ &\cdot \int_0^1 r^{p+3} (1-r^2)^{1/2(n-p-2)} dr \\ &= \frac{3}{2} \frac{\Gamma\left\{\frac{n}{2}\right\}}{\Gamma\left\{\frac{(n-p)}{2}\right\} \Gamma\left\{\frac{p}{2}+2\right\}} \\ &\cdot \int_0^1 r^{p+3} (1-r^2)^{1/2(n-p-2)} dr \\ &= \frac{3}{2} \frac{\Gamma\left\{\frac{n}{2}\right\}}{\Gamma\left\{\frac{(n-p)}{2}\right\} \Gamma\left\{\frac{p}{2}+2\right\}} \end{aligned}$$

$$\begin{aligned} &\cdot \frac{1}{2} \frac{\Gamma\left\{\frac{(n-p)}{2}\right\} \Gamma\left\{\frac{p}{2}+2\right\}}{\Gamma\left\{\frac{n}{2}+2\right\}} \\ &= \frac{3\Gamma\left\{\frac{n}{2}\right\}}{4\Gamma\left\{\frac{n}{2}+2\right\}} \\ &= \frac{3}{n(n+2)}. \end{aligned} \quad (71)$$

Similarly

$$\begin{aligned} E \{q_1^2 q_2^2\} &= C_1 \int_{\sum_{k=1}^p q_k^2 < 1} q_1^2 q_2^2 \left(1 - \sum_{k=1}^p q_k^2\right)^{1/2(n-p-2)} \\ &dq_1 \cdots dq_p \\ &= C_1 \int_0^\pi d\theta_1 \int_0^\pi d\theta_2 \cdots \int_0^\pi d\theta_{p-2} \int_0^{2\pi} d\theta_{p-1} \\ &\cdot \int_0^1 r^2 \cos^2 \theta_1 r^2 \sin^2 \theta_1 \cos^2 \theta_2 \\ &\cdot (1-r^2)^{1/2(n-p-2)} \\ &\cdot \left| \frac{\partial(q_1, \dots, q_p)}{\partial(r, \theta_1, \dots, \theta_{p-1})} \right| dr \\ &= C_1 \cdot \int_0^\pi \cos^2 \theta_1 \sin^p \theta_1 d\theta_1 \\ &\cdot \int_0^\pi \cos^2 \theta_2 \sin^{p-3} \theta_2 d\theta_2 \\ &\cdot \int_0^\pi \sin^{p-4} \theta_3 d\theta_3 \cdot \int_0^\pi \sin^{p-5} \theta_4 d\theta_4 \\ &\cdots \int_0^\pi \sin \theta_{p-2} d\theta_{p-2} \\ &\cdot \int_0^{2\pi} d\theta_{p-1} \cdot \int_0^1 r^{p+3} (1-r^2)^{1/2(n-p-2)} dr \\ &= \frac{\pi^{-p/2} \Gamma\left\{\frac{n}{2}\right\}}{\Gamma\left\{\frac{(n-p)}{2}\right\}} \cdot \frac{\pi^{1/2} \Gamma\left\{\frac{(p+1)}{2}\right\}}{2 \Gamma\left\{\frac{p}{2}+2\right\}} \\ &\cdot \frac{\pi^{1/2} \Gamma\left\{\frac{(p-2)}{2}\right\}}{2 \Gamma\left\{\frac{(p+1)}{2}\right\}} \cdot \pi^{1/2} \frac{\Gamma\left\{\frac{(p-3)}{2}\right\}}{\Gamma\left\{\frac{(p-2)}{2}\right\}} \\ &\cdot \pi^{1/2} \frac{\Gamma\left\{\frac{(p-4)}{2}\right\}}{\Gamma\left\{\frac{(p-3)}{2}\right\}} \cdots \pi^{1/2} \frac{\Gamma\{1\}}{\Gamma\left\{\frac{3}{2}\right\}} \\ &\cdot 2\pi \cdot \frac{1}{2} \frac{\Gamma\left\{\frac{(n-p)}{2}\right\} \Gamma\left\{\frac{p}{2}+2\right\}}{\Gamma\left\{\frac{n}{2}+2\right\}} \\ &= \frac{1}{n(n+2)}. \end{aligned} \quad (72)$$

Therefore, (53) and (54) are proved for the case when $n > p$. This completes the proof of Lemma 2. \blacksquare

Lemma 3: Let $\hat{\mathbf{S}}$ be the sample covariance of a set of p -dimensional vectors $\{\mathbf{x}_i\}_{i=1}^n$. If $\{\mathbf{x}_i\}_{i=1}^n$ are i.i.d. Gaussian vectors with covariance $\mathbf{\Sigma}$

$$E \left\{ \|\mathbf{x}_i\|_2^4 \mid \hat{\mathbf{S}} \right\} = \frac{n}{n+2} [2\text{Tr}(\hat{\mathbf{S}}^2) + \text{Tr}^2(\hat{\mathbf{S}})]. \quad (73)$$

Proof: For simplicity, we work with the scaled covariance matrix \mathbf{M} defined as

$$\mathbf{M} = \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T = n \hat{\mathbf{S}} \quad (74)$$

and calculate $E \left\{ \|\mathbf{x}_i\|_2^4 \mid \mathbf{M} \right\}$ instead of $E \left\{ \|\mathbf{x}_i\|_2^4 \mid \hat{\mathbf{S}} \right\}$. We are then going to prove that

$$E \left\{ \|\mathbf{x}_i\|_2^4 \mid \mathbf{M} \right\} = \frac{1}{n(n+2)} (2\text{Tr}(\mathbf{M}^2) + \text{Tr}^2(\mathbf{M})). \quad (75)$$

We use Lemma 1 and Lemma 2 to establish (75).

Let \mathbf{X} and $(\mathbf{H}, \mathbf{\Lambda}, \mathbf{Q})$ be matrices defined in Definition 1. Let \mathbf{q} be the i th column of \mathbf{Q} defined in Definition 1. Then

$$\mathbf{x}_i = \mathbf{H}\mathbf{\Lambda}\mathbf{q}. \quad (76)$$

Let

$$\mathbf{D} = \mathbf{\Lambda}^2. \quad (77)$$

Then

$$\mathbf{M} = \mathbf{X}\mathbf{X}^T = \mathbf{H}\mathbf{\Lambda}^2\mathbf{H}^T = \mathbf{H}\mathbf{D}\mathbf{H}^T \quad (78)$$

and

$$\mathbf{x}_i^T \mathbf{x}_i = \mathbf{q}^T \mathbf{\Lambda}^T \mathbf{H}^T \mathbf{H} \mathbf{\Lambda} \mathbf{q} = \mathbf{q}^T \mathbf{D} \mathbf{q}. \quad (79)$$

Therefore we have

$$E \left\{ \|\mathbf{x}_i\|_2^4 \mid \mathbf{M} \right\} = E \left\{ (\mathbf{q}^T \mathbf{D} \mathbf{q})^2 \mid \mathbf{M} \right\}. \quad (80)$$

According to Lemma 1, \mathbf{Q} is independent of \mathbf{H} and $\mathbf{\Lambda}$. Since \mathbf{q} is a function of \mathbf{Q} , \mathbf{M} and \mathbf{D} are functions of \mathbf{H} and $\mathbf{\Lambda}$, \mathbf{q} is independent of \mathbf{M} and \mathbf{D} .

From the law of total expectation

$$E \left\{ (\mathbf{q}^T \mathbf{D} \mathbf{q})^2 \mid \mathbf{M} \right\} = E \left\{ E \left\{ (\mathbf{q}^T \mathbf{D} \mathbf{q})^2 \mid \mathbf{M}, \mathbf{D} \right\} \mid \mathbf{M} \right\}. \quad (81)$$

Expand $\mathbf{q}^T \mathbf{D} \mathbf{q}$ as

$$\mathbf{q}^T \mathbf{D} \mathbf{q} = \sum_{j=1}^n d_j q_j^2 \quad (82)$$

where d_j is the j th diagonal element of \mathbf{D} . Since \mathbf{q} is independent of \mathbf{M} and \mathbf{D} , according to Lemma 2

$$\begin{aligned} & E \left\{ (\mathbf{q}^T \mathbf{D} \mathbf{q})^2 \mid \mathbf{M}, \mathbf{D} \right\} \\ &= E \left\{ \sum_{j=1}^n d_j^2 q_j^4 + \sum_{j \neq k} d_j d_k q_j^2 q_k^2 \mid \mathbf{M}, \mathbf{D} \right\} \\ &= \sum_{j=1}^n d_j^2 E \left\{ q_j^4 \right\} + \sum_{j \neq k} d_j d_k E \left\{ q_j^2 q_k^2 \right\} \\ &= \frac{1}{n(n+2)} \left(3 \sum_{j=1}^n d_j^2 + \sum_{j \neq k} d_j d_k \right) \\ &= \frac{1}{n(n+2)} (2\text{Tr}(\mathbf{D}^2) + \text{Tr}^2(\mathbf{D})). \end{aligned} \quad (83)$$

Since $\text{Tr}(\mathbf{D}) = \text{Tr}(\mathbf{M})$ and $\text{Tr}(\mathbf{D}^2) = \text{Tr}(\mathbf{M}^2)$, substituting (83) into (81), we have

$$\begin{aligned} & E \left\{ (\mathbf{q}^T \mathbf{D} \mathbf{q})^2 \mid \mathbf{M} \right\} \\ &= E \left\{ \frac{1}{n(n+2)} (2\text{Tr}(\mathbf{D}^2) + \text{Tr}^2(\mathbf{D})) \mid \mathbf{M} \right\} \\ &= E \left\{ \frac{1}{n(n+2)} (2\text{Tr}(\mathbf{M}^2) + \text{Tr}^2(\mathbf{M})) \mid \mathbf{M} \right\} \\ &= \frac{1}{n(n+2)} (2\text{Tr}(\mathbf{M}^2) + \text{Tr}^2(\mathbf{M})). \end{aligned} \quad (84)$$

Lemma 3 now allows us to prove Theorem 2. ■

Proof of Theorem 2:

Proof:

$$\begin{aligned} \hat{\Sigma}_{RBLW} &= E \left\{ \hat{\Sigma}_{LW} \mid \hat{\mathbf{S}} \right\} \\ &= E \left\{ (1 - \hat{\rho}_{LW}) \hat{\mathbf{S}} + \hat{\rho}_{LW} \hat{\mathbf{F}} \mid \hat{\mathbf{S}} \right\} \\ &= (1 - E \left\{ \hat{\rho}_{LW} \mid \hat{\mathbf{S}} \right\}) \hat{\mathbf{S}} + E \left\{ \hat{\rho}_{LW} \hat{\mathbf{F}} \mid \hat{\mathbf{S}} \right\}. \end{aligned} \quad (85)$$

Therefore we obtain the shrinkage coefficient of $\hat{\Sigma}_{RBLW}$:

$$\begin{aligned} \hat{\rho}_{RBLW} &= E \left\{ \hat{\rho}_{LW} \mid \hat{\mathbf{S}} \right\} \\ &= \frac{\sum_{i=1}^n E \left\{ \left\| \mathbf{x}_i \mathbf{x}_i^T - \hat{\mathbf{S}} \right\|_F^2 \mid \hat{\mathbf{S}} \right\}}{n^2 \left[\text{Tr}(\hat{\mathbf{S}}^2) - \frac{\text{Tr}^2(\hat{\mathbf{S}})}{p} \right]}. \end{aligned} \quad (86)$$

Note that

$$\begin{aligned} & \sum_{i=1}^n E \left\{ \left\| \mathbf{x}_i \mathbf{x}_i^T - \hat{\mathbf{S}} \right\|_F^2 \mid \hat{\mathbf{S}} \right\} \\ &= \sum_{i=1}^n E \left\{ \|\mathbf{x}_i\|_2^4 \mid \hat{\mathbf{S}} \right\} - n \text{Tr}(\hat{\mathbf{S}}^2). \end{aligned} \quad (87)$$

From Lemma 3, we have

$$\begin{aligned} & \sum_{i=1}^n E \left\{ \left\| \mathbf{x}_i \mathbf{x}_i^T - \hat{\mathbf{S}} \right\|_F^2 \mid \hat{\mathbf{S}} \right\} \\ &= \frac{n(n-2)}{n+2} \text{Tr}(\hat{\mathbf{S}}^2) + \frac{n^2}{n+2} \text{Tr}^2(\hat{\mathbf{S}}). \end{aligned} \quad (88)$$

Equation (17) is then obtained by substituting (88) into (86). ■

REFERENCES

- [1] C. Stein, "Inadmissibility of the usual estimator for the mean of a multivariate distribution," in *Proc. 3rd Berkeley Symp. Math. Statist. Prob.* 1, CA, 1956, pp. 197–206.
- [2] W. James and C. Stein, "Estimation with quadratic loss," in *Proc. 4th Berkeley Symp. Math. Statist. Probabil.*, Berkeley, CA, 1961, vol. 1, pp. 361–379.
- [3] C. Stein, "Estimation of a covariance matrix," in *Rietz Lecture, 39th Ann. Meet.*, Atlanta, GA, 1975.
- [4] L. R. Haff, "Empirical Bayes estimation of the multivariate normal covariance matrix," *Ann. Statist.*, vol. 8, no. 3, pp. 586–597, 1980.
- [5] D. K. Dey and C. Srinivasan, "Estimation of a covariance matrix under Stein's loss," *Ann. Statist.*, vol. 13, pp. 1581–1591, 1985.

- [6] R. Yang and J. O. Berger, "Estimation of a covariance matrix using the reference prior," *Ann. Statist.*, vol. 22, pp. 1195–1211, 1994.
- [7] O. Ledoit and M. Wolf, "Improved estimation of the covariance matrix of stock returns with an application to portfolio selection," *J. Empir. Finance*, vol. 10, no. 5, pp. 603–621, Dec. 2003.
- [8] O. Ledoit and M. Wolf, "A well-conditioned estimator for large-dimensional covariance matrices," *J. Multivar. Anal.*, vol. 88, no. 2, pp. 365–411, Feb. 2004.
- [9] O. Ledoit and M. Wolf, "Honey, I shrunk the sample covariance matrix," *J. Portfolio Manage.*, vol. 31, no. 1, 2004.
- [10] P. Bickel and E. Levina, "Regularized estimation of large covariance matrices," *Ann. Statist.*, vol. 36, pp. 199–227, 2008.
- [11] Y. C. Eldar and J. Chernoi, "A pre-test like estimator dominating the least-squares method," *J. Statist. Plan. Inference*, vol. 138, no. 10, pp. 3069–3085, 2008.
- [12] R. Abrahamsson, Y. Selén, and P. Stoica, "Enhanced covariance matrix estimators in adaptive beamforming," *IEEE Proc. ICASSP*, pp. 969–972, 2007.
- [13] P. Stoica, J. Li, X. Zhu, and J. Guerci, "On using a priori knowledge in space-time adaptive processing," *IEEE Trans. Signal Process.*, vol. 56, pp. 2598–2602, 2008.
- [14] J. Li, L. Du, and P. Stoica, "Fully automatic computation of diagonal loading levels for robust adaptive beamforming," *IEEE Proc. ICASSP*, pp. 2325–2328, 2008.
- [15] P. Stoica, J. Li, and T. Xing, "On spatial power spectrum and signal estimation using the pisarenko framework," *IEEE Trans. Signal Process.*, vol. 56, pp. 5109–5119, 2008.
- [16] Y. I. Abramovich and B. A. Johnson, "GLRT-based detection-estimation for undersampled training conditions," *IEEE Trans. Signal Process.*, vol. 56, no. 8, pp. 3600–3612, Aug. 2008.
- [17] J. Schäfer and K. Strimmer, "A shrinkage approach to large-scale covariance matrix estimation and implications for functional genomics," *Statist. Appl. Genet. Molec. Biol.*, vol. 4, no. 1, 2005.
- [18] S. Johh, "Some optimal multivariate tests," *Biometrika*, vol. 58, pp. 123–127, 1971.
- [19] M. S. Srivastava and C. G. Khatri, *An Introduction to Multivariate Statistics* 1979.
- [20] O. Ledoit and M. Wolf, "Some hypothesis tests for the covariance matrix when the dimension is large compared to the sample size," *Ann. Statist.*, vol. 30, no. 4, pp. 1081–1102, Aug. 2002.
- [21] M. S. Srivastava, "Singular Wishart and multivariate beta distributions," *Ann. Statist.*, vol. 31, no. 5, pp. 1537–1560, 2003.
- [22] B. Hassibi and T. L. Marzetta, "Multiple-antennas and isotropically random unitary inputs: The received signal density in closed form," *IEEE Trans. Inf. Theory*, vol. 48, no. 6, pp. 1473–1484, Jun. 2002.
- [23] F. Hiai and D. Petz, "Asymptotic freeness almost everywhere for random matrices," *Acta Sci. Math. Szeged*, vol. 66, pp. 801–826, 2000.
- [24] T. L. Marzetta and B. M. Hochwald, "Capacity of a mobile multi-antenna communication link in rayleigh flat fading," *IEEE Trans. Inf. Theory*, vol. 45, no. 1, pp. 139–157, 1999.
- [25] Y. C. Eldar and S. Shamai, "A covariance shaping framework for linear multiuser detection," *IEEE Trans. Inf. Theory*, vol. 51, no. 7, pp. 2426–2446, 2005.
- [26] R. K. Mallik, "The pseudo-Wishart distribution and its application to MIMO systems," *IEEE Trans. Inf. Theory*, vol. 49, pp. 2761–2769, Oct. 2003.
- [27] G. Letac and H. Massam, "All invariant moments of the Wishart distribution," *Scand. J. Statist.*, vol. 31, no. 2, pp. 285–318, 2004.
- [28] T. Bodnar and Y. Okhrin, "Properties of the singular, inverse and generalized inverse partitioned Wishart distributions," *J. Multivar. Anal.*, vol. 99, no. 10, pp. 2389–2405, Nov. 2008.
- [29] W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the self-similar nature of ethernet traffic," *IEEE Trans. Netw.*, vol. 2, pp. 1–15, 1994.
- [30] P. Stoica and R. Moses, *Spectral Analysis of Signals*. Upper Saddle River, NJ: Prentice-Hall, 2005.
- [31] H. L. Van Trees, *Detection, Estimation, and Modulation Theory, Part I*. New York: Wiley, 1971.
- [32] S. M. Pandit and S. Wu, *Time Series and System Analysis With Applications*. New York: Wiley, 1983.
- [33] R. S. Tsay, *Analysis of Financial Time Series*. New York: Wiley, 2005.
- [34] F. Lin *et al.*, "Sensitivity-encoded (SENSE) proton echo-planar spectroscopic imaging (PEPSI) in the human brain," *Magn. Reson. Med.*, vol. 57, pp. 249–257, 2007.
- [35] G. Derado, F. D. B. Bowman, and C. D. Kilts, "Modeling the spatial and temporal dependence in fMRI data," *Biometrics*, 2009.

- [36] S. Kotz and S. Nadarajah, *Multivariate t Distributions and Their Applications*. Cambridge, U.K.: Cambridge Univ. Press, 2004.



Yilun Chen (S'05) received the B.Eng. and M.Sc. degrees in electrical engineering from Tsinghua University, Beijing, China, in 2005 and 2007, respectively.

He is currently a Ph.D. degree candidate with the Department of Electrical Engineering and Computer Science, University of Michigan, Ann Arbor. He performed research in statistical algorithms of radar imaging with the High Speed Signal Processing and Network Research Institute, Department of Electrical Engineering, Tsinghua University, between 2005 and 2007. His current research interests

include statistical signal and image processing, machine learning, and convex optimization.



Ami Wiesel (S'02–M'09) received the B.Sc. and M.Sc. degrees in electrical engineering from Tel-Aviv University (TAU), Tel-Aviv, Israel, in 2000 and 2002, respectively, and the Ph.D. degree in electrical engineering from the Technion-Israel Institute of Technology, Haifa, Israel, in 2007.

From 2007 to 2009, he was a Postdoctoral Fellow with the Department of Electrical Engineering and Computer Science, University of Michigan, Ann Arbor. Currently, he is a faculty member with The Rachel and Selim Benin School of Computer

Science and Engineering, Hebrew University of Jerusalem, Israel.

Dr. Wiesel was a recipient of the Young Author Best Paper Award for a 2006 paper in the IEEE TRANSACTIONS ON SIGNAL PROCESSING and a Student Paper Award for the 2005 Workshop on Signal Processing Advances in Wireless Communications (SPAWC) paper. He was awarded the Weinstein Study Prize in 2002, the Intel Award in 2005, the Viterbi Fellowship in 2005 and 2007, and the Marie Curie Fellowship in 2008.

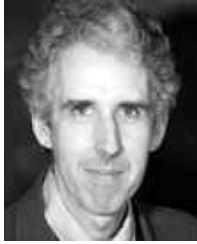


Yonina C. Eldar (S'98–M'02–SM'07) received the B.Sc. degree in physics in 1995 and the B.Sc. degree in electrical engineering in 1996, both from Tel-Aviv University (TAU), Tel-Aviv, Israel, and the Ph.D. degree in electrical engineering and computer science in 2001 from the Massachusetts Institute of Technology (MIT), Cambridge.

From January 2002 to July 2002, she was a Postdoctoral Fellow with the Digital Signal Processing Group, MIT. She is currently a Professor with the Department of Electrical Engineering, the

Technion—Israel Institute of Technology, Haifa, Israel. She is also a Research Affiliate with the Research Laboratory of Electronics, MIT, and a Visiting Professor with the Electrical Engineering and Statistics Departments, Stanford University, Stanford, CA. Her research interests are in the general areas of sampling theory, statistical signal processing, optimization methods, and their applications to biology and optics.

Dr. Eldar was in the program for outstanding students at TAU from 1992 to 1996. In 1998, she held the Rosenblith Fellowship for study in electrical engineering, MIT, and in 2000, she held an IBM Research Fellowship. From 2002 to 2005, she was a Horev Fellow of the Leaders in Science and Technology program, Technion, and an Alon Fellow. In 2004, she was awarded the Wolf Foundation Krill Prize for Excellence in Scientific Research, in 2005, the Andre and Bella Meyer Lectureship, in 2007, the Henry Taub Prize for Excellence in Research, in 2008, the Hershel Rich Innovation Award, the Award for Women with Distinguished Contributions, the Muriel and David Jacknow Award for Excellence in Teaching, and the Technion Outstanding Lecture Award, and in 2009, the Technion's Award for Excellence in Teaching. She is a member of the IEEE Signal Processing Theory and Methods Technical Committee and the Bio Imaging Signal Processing Technical Committee, an Associate Editor for the IEEE TRANSACTIONS ON SIGNAL PROCESSING, the EURASIP *Journal of Signal Processing*, the *SIAM Journal on Matrix Analysis and Applications*, and the *SIAM Journal on Imaging Sciences*, and on the Editorial Board of *Foundations and Trends in Signal Processing*.



Alfred O. Hero (S'79–M'84–SM'96–F'98) received the B.S. (*summa cum laude*) from Boston University, Boston, MA, in 1980, and the Ph.D. degree from Princeton University, Princeton, NJ, in 1984, both in electrical engineering.

Since 1984, he has been with the University of Michigan, Ann Arbor, where he is the R. Jamison and Betty Professor of Engineering. His primary appointment is with the Department of Electrical Engineering and Computer Science and he also has appointments, by courtesy, with the Department of

Biomedical Engineering and the Department of Statistics. In 2008, he was awarded the Digiteo Chaire d'Excellence, sponsored by Digiteo Research Park, Paris, located at the Ecole Supérieure d'Electricité, Gif-sur-Yvette, France. He has held other visiting positions with LIDS Massachusetts Institute of Technology (2006), Boston University (2006), I3S University of Nice, Sophia-Antipolis, France (2001), Ecole Normale Supérieure de Lyon (1999), Ecole Nationale Supérieure des Télécommunications, Paris

(1999), Lucent Bell Laboratories (1999), Scientific Research Labs of the Ford Motor Company, Dearborn, MI (1993), Ecole Nationale Supérieure des Techniques Avancées (ENSTA), Ecole Supérieure d'Electricité, Paris (1990), and M.I.T. Lincoln Laboratory (1987–1989). His recent research interests have been in detection, classification, pattern analysis, and adaptive sampling for spatio-temporal data. Of particular interest are applications to network security, multimodal sensing and tracking, biomedical imaging, and genomic signal processing.

Dr. Hero has been plenary and keynote speaker at major workshops and conferences. He has received several Best Paper awards including: a IEEE Signal Processing Society Best Paper Award (1998), the Best Original Paper Award from the *Journal of Flow Cytometry* (2008), and the Best Magazine Paper Award from the IEEE Signal Processing Society (2010). He received a IEEE Signal Processing Society Meritorious Service Award (1998), a IEEE Third Millennium Medal (2000), and a IEEE Signal Processing Society Distinguished Lecturership (2002). He was President of the IEEE Signal Processing Society (2006–2007). He sits on the Board of Directors of IEEE (2009–2011) where he is Director Division IX (Signals and Applications).