Application

2015-03-31

Vetenskapsrådet

2015-05484	Jansson, Magnus	NT-14

Information about applicant

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Project site: Avdelningen för Signalbehandling

Information about application

Call name: Forskningsbidrag Stora utlysningen 2015 (Naturvetenskap och teknikvetenskap)

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Focus: Fri

Subject area:

Project title (english): Sparse learning

Project start: 2016-01-01

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Review panel applied for: NT-14

Classification code: 20205. Signalbehandling

Keywords: sparse estimation, low rank matrix recovery, learning, compressed sensing, statistical signal processing

Funds applied for

Year:	2016	2017	2018	2019
Amount:	1,645,000	1,778,000	1,005,000	1,071,000

Descriptive data

Project info

Project title (Swedish)*

Gles inlärning

Project title (English)*

Sparse learning

Abstract (English)*

Today, with increasing sensing, storing, and computing capabilities, there is a huge need for data analytics. To be useful we need to find ways to extract useful information from the gathered data. With the rapid development of internet of things and the digitalization of the society a lot of data is generated and needs to be stored and processed. Compressive sensing may be a natural ingredient in such systems, reducing data rates already at sensor-level. Given compressed data, signal reconstruction and or inference in compressed domain needs to be carried out. We work on some ingredients in this context. Our main focus is on the reconstruction phase of compressed data using sparse learning. Sparse learning has received an enormous attention in signal processing, machine learning, statistics, control and many other fields due to its wide range of applications. In particular we will derive methods that automatically choose regularization parameters inspired by information criteria for order selection. For the multiple measurement vector case we will develop efficient sparse learning algorithms and conduct analysis. We will continue our studies on dynamic pursuit or time-varying sparse learning problems. We will also make further algorithmic studies and analysis for linear and non-linear low-rank matrix recovery problems with applications in spectral analysis, recommender systems, and crystallography.

The project will be headed by Prof. Magnus Jansson (20% activity) and carried out at the School of Electrical Engineering, Department of Signal Processing, at KTH. The research will be conducted together with a new PhD student (80% research activity over 4 years) and one existing, more senior, PhD student (80% for 2 years). As in our previous research, external collaborators will also be involved but not funded by the project.

Popular scientific description (Swedish)*

I dagens alltmer digitaliserade och uppkopplade samhälle har vi större resurser för att mäta, lagra och utföra beräkningar baserade på data. Därför finns det ett stort behov av nya metoder för dataanalys för att nyttiggöra den information som finns mer eller mindre dold i data. Eftersom det väldigt fort och lätt blir stora datamängder som måste lagras är det vettigt att försöka göra datakompression integrerat med mätningar eller insamlandet av data. Detta är ett nytt område som kallas för komprimerad mätning (eng. compressed sensing). Givet komprimerad data så måste ursprunglig data typiskt återskapas för vidare analys. Processen för att återskapa komprimerad data kallas gles inlärning (eng. sparse learning). I detta projekt studerar vi speciellt olika metoder för gles inlärning. Konceptet gles inlärning har de senaste åren väckt ett enormt intresse inom många områden såsom signalbehandling, statistik, reglerteknik, och maskininlärning. Detta är mycket beroende på att idéerna även är tillämpbara i ett bredare perspektiv. Effektiviteten hos metoder för gles inlärning beror ofta på valet av någon så kallad regulariseringsparameter.
Vi kommer studera och utveckla metoder för att automatiskt välja regulariseringsparametrar inspirerat av klassiska informationskriterier för val av modellordning. För tillämpningar med flera mätningar av samma underliggande fenomen kommer vi utveckla nya effektiva glesa inlärningsmetoder och analysera dessa. Vi kommer också studera ett mer komplicerat fall med tidsvarierande data.
Ett annat relaterat problem vi kommer angripa är att skatta dominerande principalkomponenter från komprimerad data. Detta problem har tillämpningar inom bland annat spektralanalys, rekommendationssystem för produkter och tjänster och inom kristallografi.

Project period

Number of project years*

4

Calculated project time*

2016-01-01 - 2019-12-31

Classifications

Select a minimum of one and a maximum of three SCB-codes in order of priority.

Select the SCB-code in three levels and then click the lower plus-button to save your selection.

SCB-codes*

2. Teknik > 202. Elektroteknik och elektronik > 20205. Signalbehandling

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Enter a minimum of three, and up to five, short keywords that describe your project.

Keyword 1*

sparse estimation

Keyword 2*

low rank matrix recovery

Keyword 3*

learning

Keyword 4

compressed sensing

Keyword 5

statistical signal processing

Ethical considerations

Specify any ethical issues that the project (or equivalent) raises, and describe how they will be addressed in your research. Also indicate the specific considerations that might be relevant to your application.

Reporting of ethical considerations*

The project concerns basic theoretical research and does not directly depend on ethical aspects. However, the methods developed are sometimes intended to be applied on data that may be sensitive. If we are to apply methods on real data, we are aware of that an ethical investigation (etikprövning) may need to be performed.

The project includes handling of personal data

No

The project includes animal experiments

No

Account of experiments on humans

No

Research plan

1 RESEARCH PLAN

1.1 Purpose and aim

This is a proposal for a new project with funding 10% of the principal investigator (PI) Prof. Magnus Jansson and for 1.5 PhD students (80% activity level) during 2016-2019. It is supposed to enable us to benefit from the knowledge base acquired during the ongoing project supported by VR under Contract 621-2011-5847 (PI: Magnus Jansson) entitled *"Signals and systems modeling using sparsity / Modellering av signaler och system genom användandet av gleshet"* running 2011-2015. Co-funding from KTH will be used to cover Magnus Jansson for 10% to allow at least 20% involvement in the project. The ongoing project has allowed us to enter a really exciting and extremely active field of research. We have learnt many new things and it has generated a lot of ideas. It would be satisfying to get the opportunity to bring at least some of these ideas into more substantial results by a continued VR support.

The idea is to get a kick-start of the new project by involving a senior PhD student already active in the current project the first two years, while at the same time introducing a new student to the topics. The aim is to perform basic research in signal processing as further detailed in this research program, and to train the PhD candidates to become independent researchers in a field we think is important for the future society. The long term vision of our work is to derive and analyze computationally efficient estimation methods in signal processing and related areas. A main goal is to try to develop as general tools as possible that can be applied in diverse applications and discipline areas.

Today, with increasing sensing, storing, and computing capabilities, there is a huge need for data analytics. To be useful we need to find ways to extract useful information from the gathered data. With the rapid development of internet of things and the digitalization of the society a lot of data is generated and needs to be stored and processed. Compressive sensing may be a natural ingredient in such systems, reducing data rates already at sensor-level. Given compressed data, signal reconstruction and or inference in compressed domain needs to be carried out. We work on some ingredients in this context. Our main focus is on the reconstruction phase of compressed data using sparse learning. Sparse learning has received an enormous attention in signal processing, machine learning, statistics, control and many other fields of research especially over the last seven years or so. Although much was known long before that, the ideas and computational tools were not really wide spread until more recently.

Sparse learning has many applications such as medical imaging MRI/fMRI, gene/bacteria composition analysis, proteomics, multimedia processing (image/video reconstruction, salt and pepper noise removal, segmentation text/image etc, pitch estimation, ...), crystallography, source localization (e.g., point/audio sources in room) spatial/temporal frequency estimation, regressor selection in multivariate analysis, data clustering or segmentation, trend filtering, predictive analytics, collaborative filtering in recommender systems, and so on.

In the present proposal we will not focus on any particular application but on basic research on a number of specific problems that will be introduced in the following. We will try to be quite concrete for understandability and to show the feasibility.

1.2 Survey and Project Description

In this research program we give a very brief introduction to the research area and then outline future research topics for the coming period 2016-2019. Finally, some additional information is provided according to the VR guidelines.

References in this proposal appear in two different bibliographies. References starting with an "A" appear at the end of this Research Program while references with an initial "MJ" appear in the publication list of the principal investigator.

Compressive sensing – a brief introduction There are excellent introduction articles to the subject of compressed sensing, e.g. [A1, A2, A3]. Here, we will give a very brief account of the basic idea.

Consider a vector of data z of dimension n. This may for example be the collection of n samples of a discrete time signal. Let Ψ be a matrix of orthonormal basis functions/vectors such that z can be expressed as $z = \Psi x$ for some n-dimensional parameter vector x. The data z is then said to be compressible (in this basis) if x has only very few significant nonzero coefficients. That is the data can be represented by a few basis vectors or columns of Ψ.

Now at the heart of compressed sensing is that the full data vector z can be reconstructed from a small set of observations. Typically, one assumes that only certain linear combinations of the data are measured or observed. That is, z is only indirectly observed as $y = \Phi z$ where Φ is a $m \times n$ "measurement" matrix and where m is (much) smaller than n. Hence, z is observed via its correlations with the rows of Φ. As $x = \Psi^T z$, it is common to define $A = \Phi\Psi^T$ and re-write the measurement as a function of the sparse vector x instead. We have $y = Ax$ where A is a new $m \times n$ measurement matrix. The question is when or if x, or equivalently z, can be reconstructed from y. It turns out that if A is taken as a "random matrix" then with very high probability the reconstruction is possible if m is on the order of $K\log(n)$ where K is the number of significant basis vectors required to model z. The signal reconstruction is achieved by solving a convex L1 optimization problem [A4]:

$$\min_x \; ||x||_1 \quad \text{subject to} \quad y = Ax \tag{1}$$

In words, this is interpreted as if we try to find the n-vector z that has a sparse (the sparsest) transform x while at the same time be consistent with the measurements $y = Ax$. Variations of this is possible. For example, to handle noisy data one may replace the equality constraints by $||y - Ax||_2 \leq \alpha$ for some constant α. This is sometimes referred to as basis pursuit denoising (BPDN) [A5]. Alternatively, one can use lagrange multipliers to arrive at

$$\min_x ||y - Ax||_2^2 + \lambda||x||_1 \tag{2}$$

which we will refer to as the Lasso method [A6]. Here, λ is a regularization parameter that determines the balance of data fit and sparsity. In convex optimization it is common to use the $||\cdot||_1$ norm (the sum of the magnitude of the coefficients) as a heuristic to promote sparsity of the solution. In general sparsity is measured by the $||\cdot||_0$ norm (the number of non-zero coefficients), however, this leads to non-convex and impractical solutions. We will refer to the process of recovering x (and hence z) from compressed data y as sparse learning.

In a similar fashion, the so-called nuclear norm or the sum of the singular values is used as a convex heuristic for minimizing the rank of matrices [A7, A8]. Note that the rank of a matrix is equal to the number of non-zero singular values, whereas, as mentioned, the nuclear norm is the sum of the singular values. The nuclear norm plays a similar role for minimizing the rank of matrices as the L1 norm does for minimizing the number of non-zero coefficients of a vector.

Choice of regularization parameters The main difficulty in most sparse learning methods is to choose the appropriate regularization level. In Lasso this amounts to choosing λ.

A common approach is to use cross-validation of some sort. A drawback of most such methods is that it is necessary to solve the optimization problem multiple times for different λ´s and this may be computationally infeasible. Other suggestions often rely critically on the knowledge of the noise variance in order to find reasonable upper bounds on the residual, e.g., by confidence region arguments. An example of this is the suggestion used by Candès et al in [A5] where they minimize the L1-norm of x under the constraint $||y - Ax||_2^2 \leq \sigma^2(m + 2\sqrt{2m})$ where m is the number of measurements in y. However, the noise variance σ^2 is typically unknown and difficult to estimate in under-determined settings as in compressive sensing. Another interesting approach is the so called SPARSEVA method proposed in [A9], which relies on confidence regions set by AIC/BIC type of reasoning. SPARSEVA does not need to know the noise variance but it is implicitly estimated by a least-squares step. This also implies that it does not work for under-determined problems, as the least-squares residual is zero in such cases. There are of course many other approaches in the literature that we cannot cover here.

In the proposed project we intend to research the problem of selecting appropriate regularization parameters. We have initiated some preliminary work based on ideas from classical order estimation by using information criteria such as AIC/BIC. Our focus is on the more challenging under-determined setting. Since we have more parameters than measurements, many of the classical estimation theoretical results do not directly apply. However, by judicious modifications, we believe that rules for selecting regularization levels based on AIC/BIC thinking can be devised. To show an example from our preliminary work we include a particular simulation result in Figure 1. The left plot shows amplitudes of elements of the recovered vector x

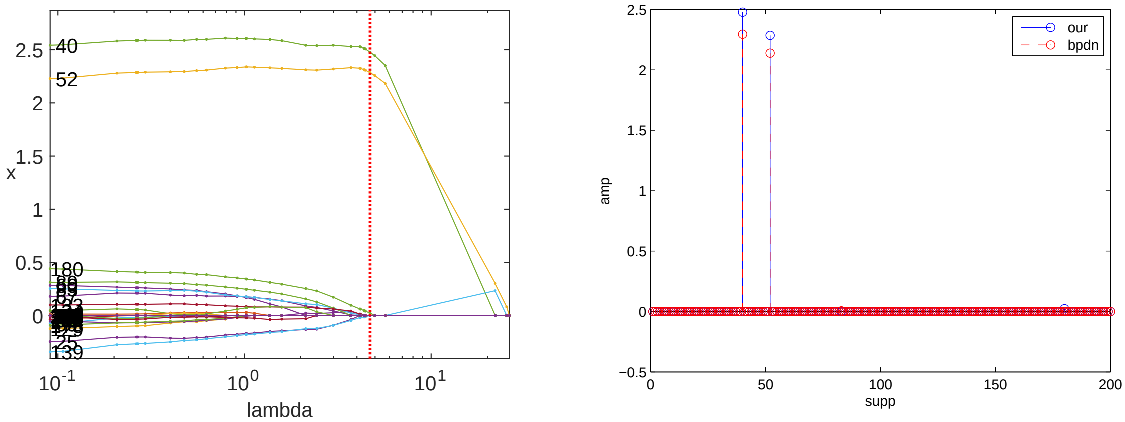

Figure 1: The left graph illustrates the recovered elements of the vector x as a function of the regularization parameter λ. The right graph displays the Lasso solution x for two different choices of regularization. The solution denoted by “our” corresponds to the particular choice of λ given by the vertical line in the left plot. The BPDN solution is obtained by using a regularization level suggested by Candès et al in [A5].

as a function of the regularization parameter λ. The true x of dimension 200 is sparse having only two non-zero elements in position 40 and 52. To recover x we use Lasso on a noisy measurement vector y of dimension 20. As can be seen in the plot, if a too large λ ($\lambda > 26.3$) is chosen we get the zero solution. When λ is decreased, some elements of the solution x become non-zero. In this case we notice that one of the first two elements selected does not correspond to the true one. However, there is a certain interval of λ-values for which the solution vector only contains non-zero elements in the correct places. The vertical dashed line in Figure 1 indicates the λ selected by our method. We emphasize that our selection of λ does not know the noise variance. In the right plot of Figure 1 we show the recovered x by using our selected λ. For comparison we also show the recovered solution obtained by the BPDN solution suggested in [A5] mentioned above. In the very preliminary tests so far, our approach seems to provide similar results as BPDN with the important benefit of not having to know the noise variance. Our approach is indeed immature and much more research is needed to better understand its properties.

We also have preliminary work on a completely different approach to the sparse vector problem and its regularization. While the approach above is based on Lasso, the other is based on maximum likelihood (ML) estimation. The idea is to re-parameterize the ML criterion using latent variables and add a penalty inspired by AIC/BIC. While not on standard form, our initial analysis shows that the final criterion to be minimized is convex in the latent variables. Again, this line of research is in its infancy but we are quite excited to see where this leads us.

Multiple measurement vector case In the noisy multiple measurement vector (MMV) problem one observes multiple snapshots

$$y(t) = Ax(t) + e(t); \quad t = 1, 2, \ldots, N. \tag{3}$$

Here, similar as before, the vectors $\{x(t)\}$ are sparse, all sharing the same support set while the amplitudes vary over "time," and $e(t)$ is noise. It is a quite common situation in applications that we make several measurements of the same underlying phenomena such as in radar or medical imaging. As before A is the "measurement matrix" or the "dictionary." In a direction of arrival (DOA) estimation problem, the columns of A would correspond to steering vectors to potential point sources. The indices of the non-zero elements of $x(t)$ then correspond to DOAs in the dictionary.

In the current project we have recently started looking into the general MMV problem using the PI's strong background in array signal processing. Similar to, e.g., the SPICE approach of Stoica and co-authors in [A10], we use a stochastic embedding of the problem, at least from an estimator design point of view. We assume that (3) are i.i.d. realizations from a zero-mean normal distribution and parameterize the problem in terms of the covariance matrices R_x of $x(t)$ and R_e of $e(t)$. In this context it is typical to assume R_x to be diagonal with a sparse diagonal vector corresponding to the powers of active sources. For the noise covariance matrix R_e, it is sometimes neglected, sometimes assumed to be a scaled identity (uniform white noise), and sometimes an arbitrary diagonal matrix (non-uniform noise). One of our contributions in [MJ78, MJ83] is to allow for a more general noise color. We only assume that R_e can be linearly parameterized, but of course sufficiently constrained such that the problem is identifiable (as an example, we studied diagonal and tri-diagonal structured R_e's). Such a generalization was quite straightforward in our setting but is highly non-trivial in, e.g., classical parametric methods for array signal processing.

In [MJ83] we generalized the basic method in [MJ78] and derived an approximate ML estimator for the MMV problem. To promote sparsity in the diagonal of R_x we added a carefully chosen L1 penalty inspired by the Square-root Lasso approach of [A11] (see also [A12]). The excellent performance of our method termed wsr-lasso is illustrated in the left graph of Figure 2. Here we use the array signal processing application to be able to benchmark the method against the classical parametric DOA Cramér-Rao lower bound (CRB) as well as the famous MUSIC high resolution parametric estimator [A13]. (It is seldom one sees this type of comparisons to alternative parametric methods and CRB's in the sparse literature.) Included is also the SPICE method of Stoica et al. [A10], which is a well cited sparse estimation approach somewhat similar to ours. The scenario consists of two uncorrelated narrowband sources of equal power that impinge from broad-side on a uniform linear array of 10 sensors. The sources are separated by 4 degrees. We observe 200 snapshots and the signal to noise ratio (SNR) is varied. Figure 2 shows the total DOA root mean square error as a function of SNR. It is clear that our method is exceedingly much better than the others and practically attains the CRB (for unorrelated sources) already at -5dB.

As mentioned above, the prevailing assumption in the covariance based sparse estimation literature is to assume R_x to be diagonal. This is also what we did in the above example. However, in applications such as array processing it is very common that signals arriving at the array are strongly correlated due to multipath propagation. If the signals are correlated while the estimator assumes a diagonal R_x it will render the DOA estimates (the estimated support of the sparse vectors) to be biased. This was illustrated in our recent paper [MJ78], see also

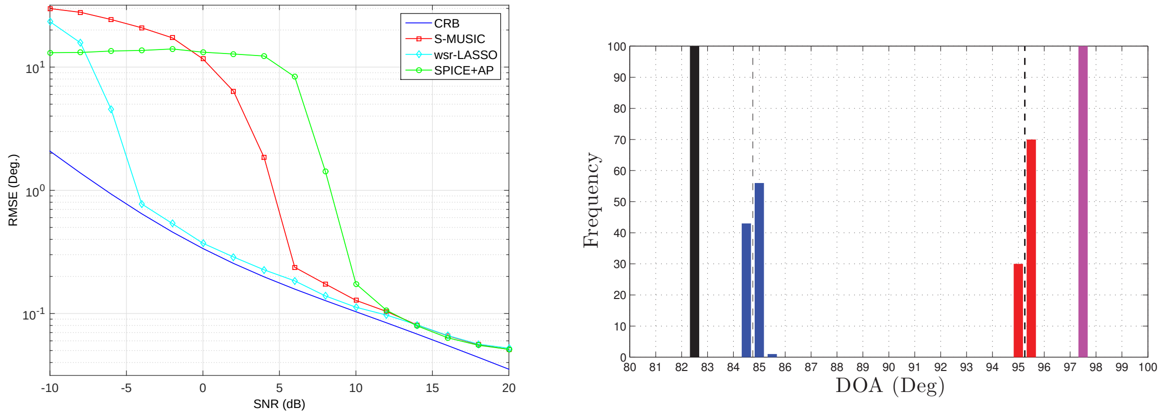

Figure 2: The left graph shows the total DOA root mean square as a function of SNR. The right graph illustrates DOA bias errors resulting from wrongly assuming R_x to be diagonal.

the right graph in Figure 2. Here we simulated two strongly correlated sources from directions $84.75°$ and $95.25°$. If an estimator assuming diagonal R_x is applied it will provide estimates corresponding to the outer bars in the figure corresponding to DOA estimates of $82.5°$ and $97.5°$, respectively. In [MJ78] we made a first attempt to modify our sparse MMV estimator to be unbiased. This attempt was successful as it provided unbiased DOA estimates as illustrated by the histogram bars around the true DOAs in Figure 2. However, this modification comes with a huge increase in computational complexity. The reason behind this is that we have to parameterize the full matrix R_x and not only its diagonal.

With this we believe we are in the forefront internationally. It should be emphasized that the array processing application is merely used here for illustration. The MMV model is very general and applicable in many contexts. In relation to MMV type of problems we see several avenues for future research:

- We believe our estimator can be improved by a different formulation of the sparse estimation step. By this we hope to be able to reduce the computational complexity while retaining the same high performance.
- We need to have a better understanding of the obtained spectrum and, if needed, detect the number of discrete sources.
- For applications like DOA/frequency estimation the dictionary is constructed by discretizing the angular sector or frequency range of interest in a finite grid. This typically leads to highly correlated dictionaries (columns of the A matrix are nearly parallel) which is known to be undesirable for sparse learning algorithms. However, as shown in the example above, our method can still resolve two closely separated sources with an excellent result, while the SPICE method does not do well in this high resolution example. To understand these differences requires more research.
- Alternative designs of the dictionary matrix could also be a possibility. There are some ongoing work in the field e.g, incorporating derivatives of steering vectors in the dictionary. We do not believe that this is the way forward, but more innovative alternatives are probably needed to get closer to optimal frames. See [MJ70] for some of our related research.
- A related line of research is to try to avoid using grid based methods to begin with. See e.g., the paper "Compressive sensing off the grid" [A14] where an atomic norm based

solution is suggested. Such approaches are limited to fourier-type dictionaries and the search is over positive definite toeplitz matrices of low rank using a nuclear norm penalty. Making an atom norm version of our wsr-Lasso approach is possible. This may be good in applications involving fourier bases. It may also be possible to generalize the idea to more general bases, e.g., using mapping or basis transformation techniques.

- We have previously developed classical spectral estimators that can benefit from prior DOA/frequency information – extending the wsr-lasso approach in this direction is rather straightforward.

- As mentioned above, we have made initial research on sparse methods that can handle signal correlation or coherence by extending the sparse penalty on the full R_x matrix [MJ78]. This implies that we go from say thousands of variables to millions. Here we need to seek for alternatives to bring the computational complexity down.

Dynamic pursuit In the dynamic pursuit problem we have a similar model as in MMV:

$$y(t) = Ax(t) + e(t). \tag{4}$$

However, here also the support of the sparse vectors $\{x(t)\}$ is time-varying. The challenge is to try to make use of some information that connects data from time to time. Clearly we want to increase performance compared to making independent analysis of each data vector separately. Dynamic pursuit could be used for video signals where in many cases there is a large redundancy between frames and hence, in such intervals, the sparsity in the transform domain should be similar from one frame to the next. It could also be used in applications involving imaging of moving objects such as in MRI of hearts where the organ is not stationary during the time it takes to collect a sufficient amount of data. Obviously, problems involving time varying DOAs or temporal frequency tracking can also be modeled as a dynamic pursuit problem. A major contributor in this field is Prof. Vaswani who received the IEEE Signal Processing Best paper award 2014 for the paper [A15].

This is in general a very challenging problem where it is important to use careful modeling, probably different from application to application, to capture the relevant information that is most useful in the joint dynamic sparse learning of $\{x(t)\}$. In a tracking problem it is likely that the support is changing slowly from time to time whereas in video data we have sudden jumps when, e.g., the scene changes. We have made some initial work on dynamic pursuit [MJ59, MJ13], but there is a huge potential for a lot more research in this area.

Greedy minimization of L1 norm As a side result of our sparse learning research we have come up with an interesting idea how to solve the L1 problem in a new greedy manner. The method (here termed GL1) is very fast for problems with really "fat" measurement matrices A as illustrated in Figure 3. Empirically we have found that the method always seems to converge to the solution of the L1 problem and believe that we now can prove this rigourously. The current version of GL1 solves the noise free L1 problem but in our future research we aim at generalizing it to also handle the noisy case.

Low-rank matrix recovery Somewhat related to the sparse vector problem, the low-rank matrix recovery (LRMR) problem is about recovering a low rank matrix from linearly sampled noisy data. The problem can be modeled as

$$y = A\,\mathrm{vec}(X) + e \tag{5}$$

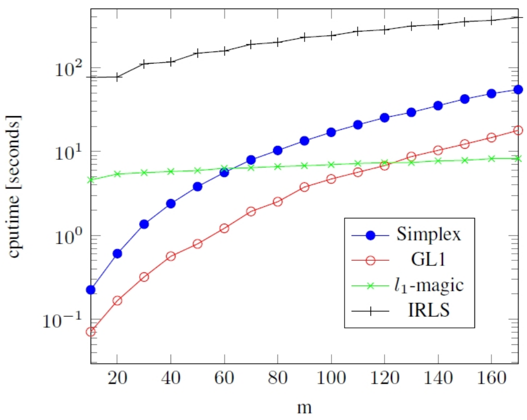

Figure 3: Comparison of computational times between different L1 solvers as a function of the number of measurements m. The dimension of x is 8000.

where $y \in \mathbb{R}^m$ is the measurement vector, $A \in \mathbb{R}^{m \times pq}$ is the sampling matrix, $X \in \mathbb{R}^{p \times q}$ is the unknown low-rank matrix to be recovered, and $e \in \mathbb{R}^m$ is noise. Here, $\mathrm{vec}()$ is the vectorization operator. The rank constraint on X is non-convex and what makes the problem difficult together with the fact that the problem often is under-sampled in the sense that $m < pq$. However, similar to the convex L1 relaxation of the vector problem, the nuclear norm can be used as a convex proxy for rank to relax the LRMR problem. This strategy has been used in numerous papers; see e.g. [A16]. A potential problem in some applications is that the nuclear penalty often do not provide sufficiently sparse or low rank solutions. This is the reason that there are multiple suggestions on how to design iteratively re-weighted nuclear norm approaches in the literature.

In the ongoing project we have mainly taken two different routes. First we used a non-convex greedy approach in which we assume that the rank r of X (or an upper bound of it) is known and explicitly used the low rank model $X = LR$, where $L \in \mathbb{R}^{p \times r}$ and $R \in \mathbb{R}^{r \times q}$. Then we solved a non-linear least squares problem in a cyclic minimization fashion with respect to L and R [MJ11, MJ33]. In these papers we actually considered a more difficult problem in which X also has linear structural constraints, e.g. being Hankel. The LRMR with Hankel constraints has applications in system identification and spectral analysis. The methods in [MJ11, MJ33] perform well in simulations and achieve an accuracy close to the CRB for the problem.

The other route we have taken is very recent and considers the LRMR with unknown rank of X. In order to try to improve on the nuclear norm based methods we have introduced a novel generalization of the celebrated Relevance Vector Machine (RVM) from machine learning [A17]. The RVM is a Bayesian learning algorithm developed for the sparse vector case. In the recently submitted paper [MJ32], we show how the ideas of RVM can be generalized to the matrix case by Bayesian modeling of X. An illustration of the performance is given in Figure 4. We have also made a first attempt to further generalize the RVM to the so called Robust Principal Component problem [A18]. See [MJ87]. We find these methods to be very interesting with a promising performance. However, many open problems remain. The approaches need to be better understood and optimized with respect to, e.g., accuracy, convergence, complexity and robustness.

We also have some exciting preliminary ideas on a phase recovery version of the LRMR problem with potential applications in crystallography.

1.2.1 Project Organization

The project will be headed by Professor Magnus Jansson and will be carried out at the School of Electrical Engineering, Department of Signal Processing, at KTH.

The research will be conducted together with a new PhD student (80% research activity over

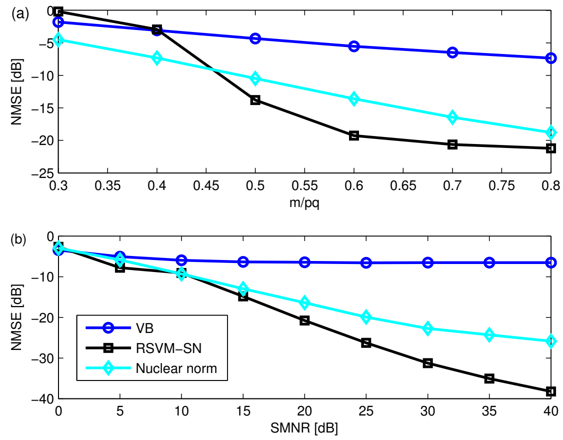

Figure 4: Performance of our Relevance Singular Vector Machine (RSVM) as compared to a nuclear norm and a variational Bayes approach.

4 years) and one existing, more senior, PhD student (80% for 2 years). The main advisor of the students will be Professor Magnus Jansson with a total involvement in the project of at least 20%. Two assistant advisors from our Department will also be engaged, namely Associate Professors Mats Bengtsson and Joakim Jalden, with expertise in convex optimization among many other things. It is also the intention to seek collaboration with other researchers with which we have excellent contacts both nationally and internationally (see, e.g., joint publications in Table 1).

The main deliverables of the project will be the education of the PhD students, material for PhD theses as well as publications at respected international conferences and in high impact journals. The open access policy will be adhered to.

1.3 Significance

The significance of this work in a wider context was briefly discussed in the introduction of this research plan. Because our main goals are to develop estimation and modeling techniques that are quite general, this implies that they can be applied in a wide area of disciplines resulting in a great impact. If we succeed in our goals to improve the performance and robustness of the algorithms, to be able to assess the quality of the models or find potential pit-falls of the methods, this should be of great and immediate practical interest.

The Department of Signal Processing is part of other more applied projects that may stimulate to new research topics in the current project. Similarly, we also expect cross transfer of results from the fundamental theoretical research to the more applied projects.

We also believe that our previous research has been well respected and have had an impact on the academic research in the respective fields of research. For example, our research on covariance matrix estimation with Kronecker structure has received interest from the statistics community and we have had contributions nominated to best paper awards in the premier signal processing conferences ICASSP and EUSIPCO, as well as in IEEE Trans. on Signal Processing (2 times). Magnus Jansson's work in system identification has been recognized by one of his algorithms being included in the MATLAB System Identification Toolbox as the default initialization method for feedback systems [MJ36]. He has also contributed to state of the art work on underwater and indoor navigation systems, and array signal processing.

Regarding the research lab: In the recent KTH international research assessment it was highlighted "Its (read: within telecommunication) single strongest aspect is the world leading research in communication theory and the physical layer of wireless, and the Access Lin-

Table 1: Recent international and national cooperation by the PI applicant.

US and Asia	
Stanford, CA	[MJ16, MJ20]
University of Illinois at Urbana-Champaign, IL	[MJ75, MJ31]
University of Minnesota, MN	[MJ73]
University of California, Irvine, CA	[MJ88]
University of California, LA, CA	[MJ30]
ABB Inc. Cleveland Ohio	[MJ89]
University of Engineering and Technology, Peshawar, Pakistan	[MJ24, MJ25]
Sharif University of Technology, Iran	[MJ78, MJ29, MJ35]
Europe	
Delft University of Technology, The Netherlands	[MJ19]
Technical University of Vienna, Vienna, Austria	[MJ2]
SUPÉLEC, France	[MJ19]
Saint Etienne University, France	[MJ12, MJ53, MJ55, MJ68]
Universitat Autonoma de Barcelona, Spain	[MJ72, MJ24, MJ25]
Universität Paderborn, Germany	[MJ25]
Imperial College London, UK	[MJ33]
Bilkent University, Ankara, Turkey	[MJ34, MJ81, MJ85, MJ86]
Turgut Ozal University, Ankara, Turkey	[MJ34, MJ85, MJ86]
Sweden	
Uppsala University, Uppsala	[MJ6, MJ8, MJ12, MJ39, MJ53, MJ55, MJ22]
Chalmers, Gothenburg	[MJ88, MJ30, MJ81]
Lund University, Lund	[MJ65]
KTH, other Departments, Stockholm	Dept. Communication Theory [MJ11, MJ13, MJ17, MJ22, MJ59, MJ66, MJ69, MJ70, MJ71, MJ74, MJ28, MJ32, MJ33, MJ79, MJ80, MJ82, MJ87], Dept. Automatic Control [MJ1, MJ3, MJ19, MJ89, MJ29, MJ32, MJ33, MJ35, MJ79], Dept. Traffic and Logistics, [MJ15, MJ43]
University of Gävle, Gävle	[MJ9, MJ10, MJ38, MJ42, MJ44, MJ46, MJ48, MJ49]
Swedish Defense Research Agency (FOI), Linköping	[MJ4]
ABB AB, Västerås	[MJ89]
Qamcom, Gothenburg	[MJ21, MJ27]

naeus Centre programme." and specifically regarding spatio-temporal wireless communications: "This is an outstanding, world leading research group – among the most respected."

Magnus Jansson is also one of the ten founding faculties of the ACCESS Linnaeus center 2006-2016, which has received very positive midterm evaluations by VR and its external experts.

To summarize, based on the above track record and recognition we believe that we can conduct significant research in an important context of a future data driven society.

1.4 Preliminary results

As mentioned before, we have had an extensive activity in this field and published numerous articles in journals and at conferences. Specific preliminary results and ideas relevant to this proposal have been accounted for in Section 1.2.

1.5 Additional information

Equipment The research conducted in this project does not have a significant experimental nature. The research group has state-of-the-art computer and network facilities required to successfully carry out this project. However, costs for continuous hardware and software investments and support are included in the budget.

International and national collaboration We have extensive national and international contacts with joint projects, joint publications, research exchanges, invited seminar series, etc. as a result. See Table 1 for a more detailed overview of recent partners.

Our students benefit greatly from this, they often spend an extended period (several months) in another research group (academic or industrial) during their studies. Establishing an international network is a natural part of our graduate education.

Being part of the ACCESS Linnaeus center also provides both a local network at KTH as well as a huge international contact network.

Other grants

The research proposed in this application is not included in any other application or project.

References

[A1] R. Baraniuk, "Compressive sensing," *Lecture notes in IEEE Signal Processing magazine*, vol. 24, no. 4, pp. 118–120, 2007.

[A2] J. Romberg, "Imaging via compressive sampling," *IEEE Signal Processing Magazine*, vol. 25, no. 2, pp. 14–20, 2008.

[A3] E. Candes and M. Wakin, "An introduction to compressive sampling," *IEEE Signal Processing Magazine*, vol. 25, no. 2, pp. 21–30, 2008.

[A4] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge Unversity Press, 2004.

[A5] E. Candès, J. Romberg, and T. Tao, "Stable signal recovery from incomplete and inaccurate measurements," *Comm. Pure Appl. Math.*, vol. 59, pp. 1207–1223, 2006.

[A6] R. Tibshirani, "Regression shrinkage and selection via the lasso," *Journal of the Royal Statistical Society (Series B)*, vol. 58, pp. 267–288, 1996.

[A7] Z. Liu and L. Vandenberghe, "Interior-point method for nuclear norm approximation with application to system identification," *SIAM Journal on Matrix Analysis and Applications*, vol. 31, no. 3, pp. 1235–1256, 2009.

[A8] M. Fazel, H. Hindi, and S. Boyd, "A rank minimization heuristic with application to mnimum order system approximation," in *Proc. of the Americal Control Conf.*, 2001.

[A9] C. Rojas and H. Hjalmarsson, "Sparse estimation based on a validation criterion," in *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on*, pp. 2825–2830, Dec 2011.

[A10] P. Stoica, P. Babu, and J. Li, "Spice: A sparse covariance-based estimation method for array processing," *Signal Processing, IEEE Transactions on*, vol. 59, pp. 629–638, Feb 2011.

[A11] A. Belloni, V. Chernozhukov, and L. Wang, "Square-root lasso: pivotal recovery of sparse signals via conic programming," *Biometrika*, vol. 98, no. 4, pp. 791–806, 2011.

[A12] P. J. Bickel, Y. Ritov, and A. B. Tsybakov, "Simultaneous analysis of lasso and dantzig selector," *Ann. Statist.*, vol. 37, pp. 1705–1732, 08 2009.

[A13] R. O. Schmidt, ""Multiple Emitter Location and Signal Parameter Estimation"," in *Proc. RADC Spectrum Estimation Workshop*, (Rome, NY), pp. 243–258, 1979.

[A14] G. Tang, B. Bhaskar, P. Shah, and B. Recht, "Compressed sensing off the grid," *Information Theory, IEEE Transactions on*, vol. 59, pp. 7465–7490, Nov 2013.

[A15] N. Vaswani and W. Lu, "Modified-cs: Modifying compressive sensing for problems with partially known support," *Signal Processing, IEEE Transactions on*, vol. 58, pp. 4595–4607, Sept 2010.

[A16] B. Recht, M. Fazel, and P. A. Parrilo, "Guaranteed minimum-rank solutions of linear matrix equations via nuclear norm minimization," *SIAM Review*, vol. 52, no. 3, pp. 471–501, 2010.

[A17] M. E. Tipping, "Sparse bayesian learning and the relevance vector machine," *J. Mach. Learn. Res.*, vol. 1, pp. 211–244, Sept. 2001.

[A18] E. J. Candès, X. Li, Y. Ma, and J. Wright, "Robust principal component analysis?," *J. ACM*, vol. 58, pp. 11:1–11:37, June 2011.

Interdisciplinarity

My application is interdisciplinary

☐

An interdisciplinary research project is defined in this call for proposals as a project that can not be completed without knowledge, methods, terminology, data and researchers from more than one of the Swedish Research Councils subject areas; Medicine and health, Natural and engineering sciences, Humanities and social sciences and Educational sciences. If your research project is interdisciplinary according to this definition, you indicate and explain this here.

Click here for more information

Scientific report

Scientific report/Account for scientific activities of previous project

The research described in this proposal is a continuation of research supported by the Swedish Research Council under Contract 621-2011-5847 (PI: Magnus Jansson) entitled "Signals and systems modeling using sparsity / Modellering av signaler och system genom användandet av gleshet". The duration of the project is 2012-01-01 – 2015-12-31, with a funding of 820 kSEK/Year.

Achieved results: In the current ongoing project we have built up our in house competence in the field, which was at least partially new to us. We are now in a good position to benefit from this and have many ideas for future research. Below we list the publications that so far have been produced in the project. The many submitted papers indicate the good ramp-up. Some of the results are further described in the research program.

Published articles in the project (2012–): We refer to the publication list of the PI Magnus Jansson.

Journal Papers: [MJ11, MJ12, MJ13, MJ14, MJ17, MJ18, MJ19, MJ21, MJ22, MJ24, MJ25, MJ27]

Submitted journal papers: [MJ28, MJ29, MJ32, MJ33]

Conference papers: [MJ59, MJ63, MJ64, MJ65, MJ68, MJ69, MJ70, MJ71, MJ72, MJ74, MJ77, MJ78, MJ79, MJ80, MJ82, MJ83]

Submitted conference paper: [MJ87]

PhD students in the project:
Dave Zachariah: Enrolled as Ph.D. student in February 2008 (activity level 80%). His Licentiate thesis was defended in April 2011 and the PhD thesis in May 2013. Employment ended in Aug. 2013. He is currently Post Doc at Uppsala University with P. Stoica. From 2012, Dave was partially funded by the project.

Petter Wirfält: Enrolled as Ph.D. student in May 2008 (activity level 80%). His PhD thesis was defended in Dec. 2013. During this time Petter was on paternal leaves corresponding to approximately 6 months. He is currently with Qamcom Research and Technology, Gothenburg, and part time Post Doc at KTH leading an ERC Proof of Concept project. Petter was partially funded by the project during 2012-2013.

Martin Sundin: Enrolled as Ph.D. student in June 2011 (activity level 80%). He is expected to defend his thesis in February 2016. Martin has in a large part been funded by the project together with a KTH EE excellence grant of 1MSEK.

Arash Owrang: Enrolled as Ph.D. student in March 2013 (activity level 80%). He is expected to defend his thesis in February 2018. Until now Arash, has in a large part been funded by the project.

Mohammadreza Malek Mohammadi: Visiting PhD student from Sharif Univeristy, Iran, employed during November 2013-April 2014. Mohammadreza did research in the project. Co-funding from KTH and ACCESS (see below) was used to cover his involvement.

Relations to the previous project: This application is an extension of the previous project specified above. As indicated in the research program, this proposal seeks a continued VR support of fundamental estimation theory research in signal processing. Some of the open problems identified in the previous project remain, and in this proposal we have also added new topics of general interest. We believe that our previous research has been successful, well respected, and internationally recognized which inspires us to seek continued support. As mentioned before, the ongoing project has enabled us to enter a new direction of research and we are now in a position to utilize the gained knowledge to explore new avenues.

Research resources: For the results reported above, the major funding has been from the VR project 621-2011-5847 (PI: Magnus Jansson), 2012-01-01 – 2015-12-31, with a funding of 820 kSEK/year. We have also had partial funding from:

- KTH (base funding and support from KTH EE excellent PhD student program, 1 MSEK to Martin Sundin)
- ACCESS, VR Linnaeus center (110MSEK total, 2006-2016) (K.H. Johansson and B. Ottersten, directors of the center, M. Jansson et al co-applicants)
- AMIMOS, ERC Advanced Research Grant (18MSEK total 2009-2013)(PI B. Ottersten, M. Jansson et al co-applicants)

Budget and research resources

Project staff

Describe the staff that will be working in the project and the salary that is applied for in the project budget. Enter the full amount, not in thousands SEK.

Participating researchers that accept an invitation to participate in the application will be displayed automatically under Dedicated time for this project. Note that it will take a few minutes before the information is updated, and that it might be necessary for the project leader to close and reopen the form.

Dedicated time for this project

	Role in the project	Name	Percent of full time
1	Applicant	Magnus Jansson	20
2	Other personnel without doctoral degree	PhD student (Owrang)	40
3	Other personnel without doctoral degree	PhD student	80

Salaries including social fees

	Role in the project	Name	Percent of salary	2016	2017	2018	2019	Total
1	Applicant	M. Jansson	10	114,000	117,000	121,000	124,000	476,000
2	Other personnel without doctoral degree	PhD Student (Owrang)	80	454,000	505,000			959,000
3	Other personnel without doctoral degree	PhD Student (New)	80	408,000	432,000	475,000	511,000	1,826,000
	Total			976,000	1,054,000	596,000	635,000	3,261,000

Other costs

Describe the other project costs for which you apply from the Swedish Research Council. Enter the full amount, not in thousands SEK.

Premises

	Type of premises	2016	2017	2018	2019	Total
1	Office	100,000	109,000	61,000	65,000	335,000
	Total	100,000	109,000	61,000	65,000	335,000

Running Costs

	Running Cost	Description	2016	2017	2018	2019	Total
1	Travel		98,000	105,000	60,000	64,000	327,000
2	IT + consumable		78,000	84,000	48,000	51,000	261,000
3	Publication		29,000	32,000	18,000	19,000	98,000
	Total		205,000	221,000	126,000	134,000	686,000

Depreciation costs

Depreciation cost	Description	2016	2017	2018	2019

Total project cost

Below you can see a summary of the costs in your budget, which are the costs that you apply for from the Swedish Research Council. Indirect costs are entered separately into the table.

Under Other costs you can enter which costs, aside from the ones you apply for from the Swedish Research Council, that the project includes. Add the full amounts, not in thousands of SEK.

The subtotal plus indirect costs are the total per year that you apply for.

Total budget

Specified costs	2016	2017	2018	2019	Total, applied	Other costs	Total cost
Salaries including social fees	976,000	1,054,000	596,000	635,000	3,261,000		3,261,000
Running costs	205,000	221,000	126,000	134,000	686,000		686,000
Depreciation costs					0		0
Premises	100,000	109,000	61,000	65,000	335,000		335,000
Subtotal	1,281,000	1,384,000	783,000	834,000	4,282,000	0	4,282,000
Indirect costs	364,000	394,000	222,000	237,000	1,217,000		1,217,000
Total project cost	1,645,000	1,778,000	1,005,000	1,071,000	5,499,000	0	5,499,000

Explanation of the proposed budget

Briefly justify each proposed cost in the stated budget.

Explanation of the proposed budget*

The PI Magnus Jansson will be involved by 20% in the project out of which we apply for VR funding for 10 %. Notice that KTH does not provide direct funding for professors' research. The funding is intended for both supervision and advancement in the field. The other 10 % will be covered by KTH base funding.

The VR budget covers the salary cost for one existing PhD-student, Arash Owrang (80% activity), for two years (2016-2017). We also apply for funding corresponding to a new PhD student (80% activity, 2016-2019). They will be employed (doktorandtjänst) and follow the doctoral salary ladder at KTH. Ideally we would also like to engage the students in more targeted research during part of their PhD studies. In this way they will gain valuable experiences that complements the basic research conducted in the VR project. Hence, depending on the future project portfolio of the Department, the applied funding may be used to fund several students part time rather than a single student full time.

Travel cost are calculated as one travel per participant per year, based on the Department's budget key (10 % on salary cost). Costs related to IT and consumable are based on the Department's budget key (8 %). Publication costs (3%) are also included, which reflects the significance of dissemination. A similar budget has been prepared for the rent (10,3%). We have also used LKP including semestertillägg of 53,2%, and salary revision 3% per year.

Indirect costs are specified as follows:

- Summa högskolegemensamma: 23,76%
- Summa skolgemensamma: 6,33%
- Summa avdelningsgemensamma: 7,26%
- Summa indirekta kostnader: 37,4%

The budget above is according to the guidelines. Funding for related activities of relevance (including procurement of equipment) will be provided by the accumulated faculty funding (positivt myndigheteskapital) according to Dnr:E-2010-0088) available at the Department of Signal Processing. If a reduced funding is granted (up to a reasonable amount), faculty funding will be secured so that a project can be adapted to the new funding level (omställningskostnader).

The research outlined in this application is not covered by other funded or applied for external project grants.

Other funding

Describe your other project funding for the project period (applied for or granted) aside from that which you apply for from the Swedish Research Council. Write the whole sum, not thousands of SEK.

Other funding for this project

Funder	Applicant/project leader	Type of grant	Reg no or equiv.	2016	2017	2018	2019

CV and publications

CV

Curriculum Vitae – Magnus Jansson (born: 1968)

1. Higher education degree

M.Sc. degree: Electrical Engineering, KTH, Dec. 1992
Tech. Lic. degree: Electrical Engineering/Automatic control, KTH, Jun. 1995

2. Doctoral degree

Ph.D. degree: Electrical Engineering/Automatic control, KTH, Oct. 1997 (*On Subspace Methods in System Identification and Sensor Array Signal Processing.*) Supervisor: Prof. Bo Wahlberg)

3. International PostDoc

TFR/STINT Postdoctoral Scholar, Dept of ECE, University of Minnesota, Minneapolis, MN, USA, Sep 1998 – Sep 1999

4. Docent appointments and professional qualification

Docent in Signal Processing, KTH, Jan. 2002 –

5. Current position

Professor of Signal Processing at KTH, (percentage research allocated for the position is not specified), Jan. 2013 –

6. Previous positions and periods of appointment

Mar 2003 – Dec 2012 Associate Professor, EE/KTH
Dec 1998 – Feb 2003 Assistant Professor, EE/KTH (on Post Doc leave until Sep 1999)
Nov 1997 – Aug 1998 Acting Associate Professor in Automatic Control, KTH

7. Interruption in research – Paternal leaves

Nov 2002 – May 2003 50%
Dec 2004 – Aug 2005 50%
Aug 2007 – Oct 2007 50%

8. Supervision

8a. Awarded degrees

1. Per Hyberg, Tech. Lic. Sep. 2001, PhD Feb. 2005 (*co-supervisor*)
2. Johan Falk, Tech. Lic. Dec. 2004 (*co-supervisor*)
3. Ingemar Nygren, PhD Dec. 2005
4. Anna Pernestål, Tech. Lic, Jun. 2007 (*co-supervisor*)
5. Isaac Skog, Tech. Lic. Dec. 2007, PhD Jan. 2010 (*co-supervisor*)
6. Karl Werner, Tech. Lic. Oct. 2005, PhD Oct. 2007
7. Samer Medawar, Tech. Lic. Feb. 2010, PhD Jun. 2012 (*co-supervisor*)
8. John-Olof Nilsson, PhD Nov. 2013 (*co-supervisor*)
9. Dave Zachariah, Tech. Lic. Apr. 2011, PhD May 2013
10. Petter Wirfält, PhD Dec. 2013

11. Ghazaleh Panahandeh, PhD Apr. 2014
12. Nafiseh Shariati, PhD Nov. 2014 (*co-supervisor*)

8b. Ongoing PhD students

13. Klas Magnusson (*co-supervisor*)
14. Martin Sundin
15. Arash Owrang
16. Arun Venkitamaran (*co-supervisor*)
17. Pol Del Aguila Pla (*co-supervisor*)

8c. Post-Doc

Dr. Mohammad Reza Gholami (Jan. 2014 –) PhD Chalmers Nov. 2013, Visiting student with Prof. Ali Sayed at UCLA 2013.

8d. Visiting PhD students

1. Sadiq Ali, Universitat Autonoma De Barcelona, Aug. 2012- Dec. 2012
2. Mohammadreza Malek Mohammadi, Sharif University of Technology, Nov. 2013 - Apr. 2014

9. Others

- Post Doc scholarships awarded from Wennergren, Hans Werthén, Foundation BLANCEFLOR Boncompagni-Ludovisi, née Bildt, and TFR/STINT 1998
- ACCESS, VR Linnaeus Centre, founding faculty 2006
- Major research funding from the Swedish research council (VR), 2001, 2005, 2009, 2011
- Member of numerous Technical Program Committees
- Local Arrangements Chair of The 16th IEEE Int. Workshop on Signal Processing Advances in Wireless Communications (SPAWC 2015), Stockholm, Sweden
- Invited session organizer at the IEEE DSP/SPE workshop Florida, Jan. 2009
- Thesis opponent at 7 occasions, member of thesis committees 15 times
- Member of Docent degree evaluation committees 2 times
- Associate member of IEEE Signal Processing SAM Technical Committee (since 2001)
- Director of undergraduate studies at the Departments of Signal processing and Communication theory (since 2004)
- Vice head of the Department of Signal Processing (since 2009).
- Acting head of the Department of Signal Processing, Aug-Dec 2010 (P. Händel on sabbatical).
- Member of Appointments committee for the KTH EES/CSC/ICS schools (2009-2011)
- Chairman of Appointments committee for the KTH EES school (2011-)
- Area chair, European Signal Processing Conference (EUSIPCO), 2011, 2012, 2013, 2014, and 2015.
- Associate Editor for EURASIP Journal on Advances in Signal Processing (since Jul. 2007).
- Associate Editor for IEEE Signal Processing Letters (Dec. 2008-2012).
- Senior Area Editor for IEEE Signal Processing Letters (2012-2014).
- Associate Editor for Elsevier Signal Processing (2015-).

Publication list

Magnus Jansson — Publications

Citation statistics and top-five papers

All citation data is taken as is from Google Scholar, March 24, 2015.

	All	Since 2010
Citations	1612	818
h-index	20	15
i10-index	45	30

Top-five cited papers:

- [MJ1]: *Number of citations: 115*, published: 1998
- [MJ36]: *Number of citations: 102*, published: 2003
- [MJ2]: *Number of citations: 91*, published: 2000
- [MJ3]: *Number of citations: 90*, published: 1996
- [MJ4]: *Number of citations: 70*, published: 2004

Top-five (*) most relevant published and accepted papers for the application: [MJ11, MJ13, MJ79, MJ82, MJ83].

1. Peer-reviewed original articles

Older top-cited papers

[MJ1] M. Jansson and B. Wahlberg. On consistency of subspace methods for system identification. *Automatica*, 34(12):1507–1519, Dec. 1998. *Number of citations: 115.*

[MJ2] D. Bauer and M. Jansson. Analysis of the asymptotic properties of the MOESP type of subspace algorithms. *Automatica*, 36(4):497–509, Apr. 2000. *Number of citations: 91.*

[MJ3] M. Jansson and B. Wahlberg. A linear regression approach to state-space subspace system identification. *Signal Processing*, 52(2):103–129, July 1996. *Number of citations: 90.*

[MJ4] I. Nygren and M. Jansson. Terrain navigation for underwater vehicles using the correlator method. *IEEE Journal of Oceanic Engineering*, 29(3):906–915, Jul. 2004. *Number of citations: 70.*

2007-2015

[MJ5] K. Werner and M. Jansson. DOA estimation and detection in colored noise using additional noise-only data. *IEEE Transactions on Signal Processing*, 55(11):5309–5322, Nov. 2007. *Number of citations: 14.*

[MJ6] K. Werner, M. Jansson, and P. Stoica. On estimation of covariance matrices with Kronecker product structure. *IEEE Transactions on Signal Processing*, 56(2):478–491, Feb. 2008. *Number of citations: 68.*

[MJ7] K. Werner and M. Jansson. Estimating MIMO channel covariances from training data under the Kronecker model. *Signal Processing*, 89(1):1–13, 2009. *Number of citations: 24*.

[MJ8] P. Stoica and M. Jansson. On maximum likelihood estimation in factor analysis–An algebraic derivation. *Signal Processing*, 89:1260–1262, Jun. 2009. *Number of citations: 6*.

[MJ9] S. Medawar, P. Händel, N. Björsell, and M. Jansson. Input-dependent integral nonlinearity modeling for pipelined analog digital converters. *IEEE Transactions on Instrumentation and Measurements*, 59(10):2609–2620, Oct. 2010. ISSN 0018-9456. *Number of citations: 15*.

[MJ10] S. Medawar, P. Händel, N. Björsell, and M. Jansson. Postcorrection of pipelined analog-digital converters based on input dependent integral nonlinearity modeling. *IEEE Transactions on Instrumentation and Measurements*, 60(10):3342 – 3350, Oct. 2011. ISSN 0018-9456. *Number of citations: 15*.

[MJ11] D. Zachariah, M. Sundin, M. Jansson, and S. Chatterjee. Alternating least-squares for low-rank matrix reconstruction. *IEEE Signal Processing Letters*, 19(4):231 – 234, Apr. 2012. ISSN 1070-9908. *Number of citations: 20*.

[MJ12] P. Wirfält, G. Bouleux, M. Jansson, and P. Stoica. Optimal prior knowledge-based direction of arrival estimation. *Signal Processing, IET*, 6(8):731–742, 2012. *Number of citations: 3*.

[MJ13] D. Zachariah, S. Chatterjee, and M. Jansson. Dynamic iterative pursuit. *IEEE Trans. on Signal Processing*, 60(9):4967–4972, Sep. 2012. ISSN 1053-587X. *Number of citations: 13*.

[MJ14] D. Zachariah, I. Skoog, M. Jansson, and P. Händel. Bayesian estimation with distance bounds. *IEEE Signal Processing Letters*, 19(12):880–83, Dec. 2012. *Number of citations: 9*.

[MJ15] X. Ma and M. Jansson. A model identification scheme for driver-following dynamics in road traffic. *Control Engineering Practice*, 21(6):807 – 817, 2013. ISSN 0967-0661. *Number of citations: 2*.

[MJ16] S. Medawar, P. Händel, B. Murmann, N. Björsell, and M. Jansson. Dynamic calibration of undersampled pipelined adcs by frequency domain filtering. *IEEE Transactions on Instrumentation and Measurement*, 62(7):1882–1891, 2013. ISSN 0018-9456. *Number of citations: 2*.

[MJ17] D. Zachariah, P. Wirfält, M. Jansson, and S. Chatterjee. Line spectrum estimation with probabilistic priors. *Signal Processing*, 93(11):2969–2974, 2013. ISSN 0165-1684. *Number of citations: 4*.

[MJ18] D. Zachariah, M. Jansson, and M. Bengtsson. Utilization of noise-only samples in array processing with prior knowledge. *IEEE Signal Processing Letters*, 20(9):865–868, Sep. 2013. *Number of citations: 1*.

[MJ19] D. Katselis, C. Rojas, M. Bengtsson, E. Björnson, X. Bombois, N. Shariati, M. Jansson, and H. Hjalmarsson. Training sequence design for mimo channels: An application-oriented approach. *EURASIP Journal on Wireless Communications and Networking*, (1):245–276, Oct. 2013. *Number of citations: 8*.

[MJ20] S. Medawar, B. Murmann, P. Händel, N. Björsell, and M. Jansson. Static integral nonlinearity modeling and calibration of measured and synthetic pipeline analog-digital converters. *IEEE Transactions on Instrumentation and Measurement*, 63(3):502–511, 2014. *Number of citations: 2*.

[MJ21] P. Wirfält and M. Jansson. On Kronecker and linearly structured covariance matrix estimation. *IEEE Trans. on Signal Processing*, 62(6):1536–1547, Mar. 2014. *Number of citations: 1*.

[MJ22] D. Zachariah, N. Shariati, M. Bengtsson, M. Jansson, and S. Chatterjee. Estimation for the linear model with uncertain covariance matrices. *IEEE Trans. on Signal Processing*, 62(6):1525–1535, Mar. 2014. *Number of citations: 1*.

[MJ23] G. Panahandeh and M. Jansson. Vision-aided inertial navigation based on ground plane feature detection. *IEEE/ASME Trans. on Mechatronics*, 19(4):1206–1215, Aug. 2014. ISSN 1083-4435. *Number of citations: 4*.

[MJ24] S. Ali, M. Jansson, G. Seco-Granados, and J. López-Salcedo. Kronecker-based fusion rule for cooperative spectrum sensing with multi-antenna receivers. *Electronics*, 3(4):675–688, 2014. ISSN 2079-9292. *Number of citations: -*.

[MJ25] S. Ali, D. Ramirez, M. Jansson, G. Seco-Granados, and J. Lopez-Salcedo. Multi-antenna spectrum sensing by exploiting spatio-temporal correlation. *EURASIP Journal on Advances in Signal Processing*, 2014(1):160, 2014. ISSN 1687-6180. *Number of citations: 1*.

[MJ26] G. Panahandeh, M. Jansson, and P. Händel. Calibration of an imu-camera cluster using planar mirror reflection and its observability analysis. *IEEE Transactions on Instrumentation and Measurement*, 64(1):75–88, Jan. 2015. ISSN 0018-9456. *Number of citations: -*.

[MJ27] P. Wirfält and M. Jansson. Prior-exploiting direction-of-arrival algorithms for partially uncorrelated source signals. *Signal Processing*, 109:182 – 192, 2015. ISSN 0165-1684. *Number of citations: 2*.

Submitted papers

(Included to be able to cite them in the application)

[MJ28] M. Sundin, S. Chatterjee, and M. Jansson. Combined modeling of sparse and dense noise for improvement of relevance vector machine. *IEEE Trans. on Signal Processing*, 2014. Submitted.

[MJ29] M. Malek-Mohammadi, A. Koochakzadeh, M. Babaie-Zadeh, M. Jansson, and C. Rojas. Succesive concave sparsity approximation: Near-oracle performance in a wide range of sparsity levels. *IEEE Trans. on Signal Processing*, 2014. Submitted.

[MJ30] M. Gholami, M. Jansson, E. Ström, and A. Sayed. Diffusion estimation over cooperative multi-agent networks with missing data. *IEEE Transactions on Signal and Information Processing over Networks*, 2015. Submitted.

[MJ31] G. Panahandeh, S. Huthchinson, P. Händel, and M. Jansson. Planar-based visual inertial navigation: Observability analysis and motion estimation. *Journal of Intelligent and Robotic Systems*, Jan. 2015. Submitted.

[MJ32] M. Sundin, C. Rojas, S. Chatterjee, and M. Jansson. Bayesian learning for low-rank matrix reconstruction. *IEEE Trans. on Signal Processing*, 2015. Submitted.

[MJ33] K. Li, M. Sundin, C. Rojas, S. Chatterjee, and M. Jansson. Alternating strategies with internal admm for low-rank matrix reconstruction. *Signal Processing*, 2015. Submitted.

[MJ34] S. Gezici, M. Gholami, S. Bayram, and M. Jansson. Jamming of wireless localization systems. *IEEE Trans. on Wireless Communications*, 2015. Submitted.

[MJ35] M. Malek-Mohammadi, C. Rojas, M. Jansson, and M. Babaie-Zadeh. Upper bounds on the error of sparse vector and low rank matrix recovery, 2015. Under revision.

2. Peer-reviewed conference contributions

Older top-cited paper

[MJ36] M. Jansson. Subspace identification and ARX modeling. In *IFAC Symp. on System Identification*. Rotterdam, The Netherlands, Aug. 2003. *Number of citations: 102*.

2007-2015

[MJ37] I. Nygren and M. Jansson. FDM and FEM filters in terrain navigation. In *The Institute of Navigation: National Technical Meeting*, pp. 1155–1166. San Diego, CA, Jan. 22-24 2007. *Number of citations: 3*.

[MJ38] P. Händel, N. Björsell, and M. Jansson. Model based dynamic characterization of analog-digital converters at radio frequency. In *ISSPA'07 - International Symposium on Signal Processing and its Applications*. Sharjah, United Arab Emirates, Feb. 12-15 2007. *Number of citations: 17*.

[MJ39] K. Werner, M. Jansson, and P. Stoica. Kronecker structured covariance matrix estimation. In *IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, vol. 3, pp. III:825–828. Honolulu, Hawaii, Apr. 15-20 2007. *Number of citations: 6*.

[MJ40] P. Händel, N. Björsell, M. Jansson, and S. Medawar. Modeling the dynamics of analog-digital converters at radio frequency. In *The Conference on RF Measurement Technology for State of The Art Production and Design*. Gävle, Sweden, Sep. 2007.

[MJ41] K. Werner and M. Jansson. Estimation of kronecker structured channel covariances using training data. In *Proceedings European Signal Processing Conference*. Poznan, Poland, Sep. 3-7 2007. *Number of citations: 11*.

[MJ42] S. Medawar, N. Björsell, P. Händel, and M. Jansson. Dynamic characterization of analog-digital-converters non-linearities. In *Proceedings Mosharaka Multi-Conference on Communications, Networking and Information Technology*. Amman, Jordan, Sep. 6-8 2007. *Number of citations: 6*.

[MJ43] X. Ma and M. Jansson. Model estimation for car-following dynamics based on adaptive filtering approach. In *IEEE Intelligent Transportation Systems Conference*, pp. 824 – 829. Seattle, Washington, Oct. 2007. *Number of citations: 2*.

[MJ44] S. Medawar, P. Händel, N. Björsell, and M. Jansson. ADC characterization by dynamic integral nonlinearity. In *Proc. 13th Workshop on ADC Modeling and Testing, Florence, Italy*, Sep. 2008. *Number of citations: 8*.

[MJ45] M. Jansson, P. Wirfält, K. Werner, and B. Ottersten. ML estimation of covariance matrices with Kronecker and persymmetric structure. In *13th IEEE Digital Signal Processing Workshop*. Marco Island, FL, Jan. 2009. *Number of citations: 9*.

[MJ46] S. Medawar, P. Händel, N. Björsell, and M. Jansson. Model order determination and segmentation of analog-digital converters integral non linearity. In *IEEE International Instrumentation and Measurement Technology Conference*. Austin, TX, May 2010. *Number of citations: 1*.

[MJ47] D. Zachariah and M. Jansson. Camera-aided inertial navigation using epipolar points. In *IEEE/ION conf. on Position Location and Navigation System (PLANS)*. Indian Wells/Palm Springs, CA, May 2010. *Number of citations: 20*.

[MJ48] S. Medawar, P. Händel, N. Björsell, and M. Jansson. Pipelined analog-digital converters integral nonlinearity modeling for post-correction. In *IMEKO 15th International workshop on ADC*. Kosice, Slovakia, Sep. 2010. *Number of citations: 1*.

[MJ49] N. Björsell, P. Händel, M. Jansson, and S. Medawar. Improved estimate of parametric

models for analogue to digital converters by using weighted integral nonlinearity data. In *IMEKO 15th International workshop on ADC*, pp. 62–. Kosice, Slovakia, sep 2010. *Number of citations: -.*

[MJ50] G. Panahandeh, I. Skog, and M. Jansson. Calibration of the accelerometer triad of an inertial measurement unit, maximum likelihood estimation and cramer-rao bound. In *International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. Zurich, Switzerland, Sep. 2010. *Number of citations: 21.*

[MJ51] D. Zachariah and M. Jansson. Joint calibration of an inertial measurement unit and coordinate transformation parameters using a monocular camera. In *International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. Zurich, Switzerland, Sep. 2010. *Number of citations: 9.*

[MJ52] P. Wirfält and M. Jansson. On toeplitz and kronecker structured covariance matrix estimation. In *Proceedings IEEE Sensor Array and Multichannel Signal Processing Workshop*, pp. 185 – 188. Israel, Oct. 2010. ISBN 978-1-4244-9395-1. *Number of citations: 11.*

[MJ53] P. Wirfält, M. Jansson, G. Bouleux, and P. Stoica. Prior knowledge-based direction of arrival estimation. In *Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*, pp. 2540–2543. Prague, Czech Republic, May 2011. *Number of citations: 7.*

[MJ54] D. Zachariah and M. Jansson. Self-motion and wind velocity estimation for small-scale UAVs. In *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 1166 –1171. Shanghai, China, May 2011. *Number of citations: 5.*

[MJ55] P. Wirfält, G. Bouleux, M. Jansson, and P. Stoica. Subspace-based frequency estimation utilizing prior information. In *IEEE Workshop on Statistical Signal Processing*, pp. 533 –536. Nice, France, Jun. 2011. *Number of citations: 10.*

[MJ56] G. Panahandeh and M. Jansson. Imu-camera self-calibration using planar mirror reflection. In *Int. Conf. on Indoor Positioning and Indoor Navigation (IPIN)*, pp. 1 –7. Zurich, Switzerland, Sep. 2011. *Number of citations: 15.*

[MJ57] G. Panahandeh and M. Jansson. Vision-aided inertial navigation using planar terrain features. In *IEEE International Conference on Robot, Vision and Signal Processing*. Kaohsiung, Taiwan, Nov. 2011. *Number of citations: 8.*

[MJ58] G. Panahandeh, D. Zachariah, and M. Jansson. Mirror based imu-camera and internal camera calibration. In *IEEE International Conference on Robot, Vision and Signal Processing*. Kaohsiung, Taiwan, Nov. 2011. *Number of citations: 4.*

[MJ59] D. Zachariah, S. Chatterjee, and M. Jansson. Dynamic subspace pursuit. In *Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*. Kyoto, Japan, Mar. 2012. *Number of citations: 3.*

[MJ60] J.-O. Nilsson, D. Zachariah, M. Jansson, and P. Händel. Real-time implementation of visual-aided inertial navigation using epipolar constraints. In *IEEE/ION Position Location and Navigation Symposium (PLANS)*. Myrtle Beach, South Carolina, Apr. 2012. *Number of citations: 5.*

[MJ61] G. Panahandeh, D. Zachariah, and M. Jansson. Exploiting ground plane constraints for visual-aided inertial navigation. In *IEEE/ION Position Location and Navigation Symposium (PLANS)*. Myrtle Beach, South Carolina, Apr. 2012. *Number of citations: 12.*

[MJ62] D. Zachariah and M. Jansson. Fusing visual tags and inertial information for indoor navigation. In *IEEE/ION Position Location and Navigation Symposium (PLANS)*. Myrtle Beach, South Carolina, Apr. 2012. *Number of citations: 3.*

[MJ63] M. Sundin and M. Jansson. Low rank matrix reconstruction in system identification.

In *Reglermöte*. Uppsala, Sweden, Jun. 2012.

[MJ64] P. Wirfält and M. Jansson. Robust prior-based direction of arrival estimation. In *IEEE Statistical Signal Processing Workshop (SSP)*, pp. 81–84. Ann Arbor, Michigan, Aug. 2012. *Number of citations: 4*.

[MJ65] E. Gudmundson, P. Wirfält, A. Jakobsson, and M. Jansson. An esprit-based parameter estimator for spectroscopic data. In *IEEE Statistical Signal Processing Workshop (SSP)*. Ann Arbor, Michigan, Aug. 2012. *Number of citations: 6*.

[MJ66] G. Panahandeh, N. Mohammadiha, and M. Jansson. Ground plane feature detection in mobile vision-aided inertial navigation. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. Vilamoura, Algarve, Portugal, Oct. 2012. *Number of citations: 6*.

[MJ67] G. C. Barcelo, G. Panahandeh, and M. Jansson. Image-based floor segmentation in visual aided inertial navigation. In *IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*. Minneapolis, MN, USA, May 2013. *Number of citations: 2*.

[MJ68] P. Wirfält, M. Jansson, and G. Bouleux. Prior-exploiting direction-of-arrival algorithm for partially uncorrelated source signals. In *Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*. Vancouver, Canada, May 2013. *Number of citations: 2*.

[MJ69] D. Zachariah, S. Chatterjee, and M. Jansson. Iteratively reweighted least squares for reconstruction of low-rank matrices with linear structure. In *Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*, pp. 3972–3976. Vancouver, Canada, May 2013. *Number of citations: 1*.

[MJ70] M. Sundin, D. Sundman, and M. Jansson. Beamformers for sparse recovery. In *Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*. Vancouver, Canada, May 2013. *Number of citations: 2*.

[MJ71] M. Sundin, M. Jansson, and S. Chatterjee. Conditional prior based lmmse estimation of sparse signals. In *European Signal Processing Conference (EUSIPCO)*. Marrakech, Morocco, Sep. 2013. *Number of citations: -*.

[MJ72] S. Ali, M. Jansson, G. Seco-Granados, and J. Lopez-Salcedo. Novel collaborative spectrum sensing based on spatial covariance structure. In *European Signal Processing Conference (EUSIPCO)*. Marrakech, Morocco, Sep. 2013. *Number of citations: 2*.

[MJ73] G. Panahandeh, C. Guo, M. Jansson, and S. Roumeliotis. Observability analysis of a vision-aided inertial navigation system using planar features on the ground. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. Tokyo, Japan, Nov. 2013. *Number of citations: 1*.

[MJ74] D. Zachariah, M. Jansson, and S. Chatterjee. Enhanced capon beamformer using regularized covariance matching. In *IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*. Saint Martin, Dec. 2013. *Number of citations: -*.

[MJ75] G. Panahandeh, M. Jansson, and S. Hutchinson. Imu-camera data fusion: Horizontal plane observation with explicit outlier rejection. In *International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. Montbeliard-Belfort, France, Oct. 2013. *Number of citations: 2*.

[MJ76] G. Panahandeh, P. Händel, and M. Jansson. Observability analysis of mirror-based imu-camera self-calibration. In *International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. Montbeliard-Belfort, France, Oct. 2013. *Number of citations: 1*.

[MJ77] A. Venkitaraman and M. Jansson. On estimation of covariance matrices modeled as a

sum of kronecker products. In *PLS 2014 8th International Conference on Partial Least Squares and Related Methods*, pp. 171–172. Paris, France, May 2014. *Number of citations: -.*

[MJ78] M. Malek-Mohammadi, M. Jansson, A. Owrang, A. Koochakzadeh, and M. Babaie-Zadeh. Doa estimation in partially correlated noise using low-rank/sparse matrix decomposition. In *IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM)*. La Coruna, Spain, Jun. 2014. *Number of citations: 2.*

[MJ79] M. Sundin, S. Chatterjee, M. Jansson, and C. Rojas. Relevance singular vector machine for low rank matrix sensing. In *International Conference on Signal Processing and Communications (SPCOM)*. Bangalore, India, Jul. 2014. *Number of citations: 1.*

[MJ80] M. Sundin, S. Chatterjee, and M. Jansson. Combined modeling of sparse and dense noise improves bayesian RVM. In *22nd European Signal Processing Conference (EUSIPCO)*. Lisbon, Portugal, Sep. 2014. *Number of citations: -.*

[MJ81] M. Gholami, S. Gezici, H. Wymeersch, E. Ström, and M. Jansson. Characterizing the worst-case position error in bearing-only target localization. In *Proc. 12th Annual Workshop on Positioning, Navigation and Communication (WPNC)*. Dresden, Germany, Mar. 2015. *Number of citations: -.*

[MJ82] M. Sundin, S. Chatterjee, and M. Jansson. Greedy minimization of l1-norm with high empirical success. In *Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*. Brisbane, Australia, Apr. 2015.

[MJ83] A. Owrang and M. Jansson. Weighted covariance matching based square root lasso. In *Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*. Brisbane, Australia, Apr. 2015.

[MJ84] M. Gholami, S. Dwivedi, M. Jansson, and P. Händel. Ranging without time stamps exchanging. In *Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*. Brisbane, Australia, Apr. 2015.

[MJ85] S. Gezici, M. Gholami, S. Bayram, and M. Jansson. Optimal jamming of wireless localization systems. In *IEEE ICC 2015 - Workshop on Advances in Network Localization and Navigation*. London, United Kingdom, Jun. 2015.

Submitted papers

[MJ86] S. Gezici, S. Bayram, M. Gholami, and M. Jansson. Optimal jammer placement in wireless localization networks. In *The 16th IEEE Int. Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*. Stockholm, Sweden, Jun. 2015. Submitted.

[MJ87] M. Sundin, S. Chatterjee, and M. Jansson. Bayesian learning for robust principal component analysis. In *European Signal Processing Conference (EUSIPCO)*. Nice, France, Aug. 2015. Submitted.

5. Books and book chapters

[MJ88] M. Jansson, B. Ottersten, M. Viberg, and A. L. Swindlehurst. Optimal subspace techniques for DOA estimation in the presence of noise and model errors. In H. Bölcskei, D. Gesbert, C. Papadias, and A. J. van der Veen, eds., *Space-Time Wireless Systems:*

From Array Processing to MIMO Communications. Cambridge University Press, 2006. *Number of citations: 1*.

[MJ89] B. Wahlberg, M. Jansson, T. Matsko, and M. Molander. Experiences from subspace system identification - comments from process industry users and researchers. In S. P. A. Chiuso, A. Ferrante, ed., *Modeling, Estimation and Control, Lecture Notes in Information and Control Sciences*, pp. 315–327. Springer, Oct. 2007. ISBN 9783540735694. *Number of citations: 15*.

[MJ90] P. Händel, R. Ottoson, H. Hjalmarsson, and M. Jansson. *Signal Theory*. signalteori.nu, Stockholm, 2007. ISBN 91-974087-2-7. Edited and Translated to English 2007 by Magnus Jansson.

CV

Name: Magnus Jansson	**Doctorial degree:** 1997-10-30
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Gender: Male	**Employer:** Kungliga Tekniska högskolan

Research education

Dissertation title (swe)
Om underrumsmetoder i systemidentifiering och gruppantennsignalbehandling

Dissertation title (en)
On Subspace Methods in System Identification and Sensor Array Signal Processing

Organisation	Unit	Supervisor
Kungliga Tekniska Högskolan, Sweden Sweden - Higher education Institutes	Avdelningen för Reglerteknik	Bo Wahlberg

Subject doctors degree	ISSN/ISBN-number	Date doctoral exam
20202. Reglerteknik	ISSN 0347–1071	1997-10-30

Publications

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Jansson, Magnus has not added any publications to the application.

Register

Terms and conditions

The application must be signed by the applicant as well as the authorised representative of the administrating organisation. The representative is normally the department head of the institution where the research is to be conducted, but may in some instances be e.g. the vice-chancellor. This is specified in the call for proposals.

The signature*from the applicant*confirms that:

- the information in the application is correct and according to the instructions form the Swedish Research Council
- any additional professional activities or commercial ties have been reported to the administrating organisation, and that no conflicts have arisen that would conflict with good research practice
- that the necessary permits and approvals are in place at the start of the project e.g. regarding ethical review.

The signature *from the administrating organisation* confirms that:

- the research, employment and equipment indicated will be accommodated in the institution during the time, and to the extent, described in the application
- the institution approves the cost-estimate in the application
- the research is conducted according to Swedish legislation.

The above-mentioned points must have been discussed between the parties before the representative of the administrating organisation approves and signs the application.

Project out lines are not signed by the administrating organisation. The administrating organisation only sign the application if the project outline is accepted for step two.

Applications with an organisation as applicant is automatically signed when the application is registered.