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2015-05006	McKelvey, Tomas	NT-14

Information about applicant

Name: Tomas McKelvey

Doctorial degree: 1995-05-05

Birthdate: 19660407

Academic title: Professor

Gender: Male

Employer: Chalmers tekniska högskola

Administrating organisation: Chalmers tekniska högskola

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Descriptive data

Project info

Project title (Swedish)*

Gleshetsbaserad inlärning av parametriskt separabla modeller

Project title (English)*

Sparsity-Based Learning of Parametric Separable Models

Abstract (English)*

In many technological areas, the reliability of the applied methods highly depends on models as the mathematical descriptions of their corresponding environment. Although the models are commonly simplified in favor of their utility, increasing demand for higher reliability naturally calls for more sophisticated models. In the field of signal processing, the so-called sparsity-based models has recently gained high attention. Apart from the connection of the sparsity-based models to a large variety of different applications, their popularity is mainly due to the invention of highly efficient and reliable mathematical computation techniques, which are shown to solve difficult sparsity-based problems under mild assumptions. Due to their computational stability, the sparsity-based techniques are useful in treating not only large size problems, but also a family of challenging problems of a small dimension, called parametric estimation. Still, the reliability of the sparsity-based approach depends on the accurate choice of a sparse model.
This project concerns a more recent problem of selecting a proper sparse model, based on a set of observations. As a sparse model is identified by its so-called dictionary, this problem is often referred to as dictionary learning. Through this research, we aim to obtain generic bounds on the performance of dictionary learning, analyze the existing techniques and compare the result to the generic bounds. Further, we aim to improve the existing techniques guided by the results obtained by our analysis. Here, the emphasize is on the application of dictionary learning to parametric estimation problems. We have taken initial steps in the above direction and identified interesting properties, as well as fundamental deficiencies in the existing techniques. Accordingly, some suggestions for further improvement have also been obtained.

Popular scientific description (Swedish)*

Denna forskning handlar om metoder för automatisk inlärning av modeller för signalbehandling. En modell är en matematisk beskrivning av en omgivning som ger möjlighet att manipulera data, dra slutsatser om icke direkt observerade fenomen och prediktera framtida egenskaper hos ett system. En noggrann modell kan ibland härledas från fysikaliska principer eller enbart erhållas genom experiment och leder ofta till en komplicerad beskrivning. Inom många tekniska områden brukar dock noggrannheten tillåtas minska för att förenkla modellen, ofta på grund av begränsad beräkningskapacitet. Processen för att skapa sådana approximativa modeller från observationer benämns modellinlärning eller systemidentifiering.

I många tillämpningar är en speciell typ av modell, så kallade separabla eller glesa, av stor vikt. Under de senaste årtiondena har en ny matematisk teknik introducerats som leder till en förenkling av hanteringen av denna typ av glesa modeller. Dessa metoder har lett till en signifikant förbättring av kvaliteten hos signalbehandlingen, under förutsättning att modellen är helt känd. I praktiken måste dock den glesa modellen skapas från observerade data som innehåller osäkerheter. Alltså, huvuddelen av detta arbete är att studera metoder för inlärning av glesa modeller. Generella frågor av typen som vad som är den bästa prestandan kommer att besvaras i forskningen. Dessutom kommer prestandan för existerande metoder att studeras och jämföras med bästa möjliga prestanda, samt undersöka vägar för att förbättra metoderna.

Project period

Number of project years*

2

Calculated project time*

2016-01-01 - 2017-12-31

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*

Parametric Modeling

Keyword 3*

Array Signal Processing

Keyword 4

Dictionary Learning

Keyword 5

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*

This project has no ethical implications.

The project includes handling of personal data

No

The project includes animal experiments

No

Account of experiments on humans

No

Research plan

Sparsity-Based Learning
of
Parametric Separable Models

1 Purpose and Aims

The last few decades have witnessed the emergence of sparsity-based techniques in a variety of different research fields. Currently, a large body of research is devoted to developing and studying these techniques in a range of applications, from machine learning and data acquisition to parameter estimation, system identification and inverse problems. This is mainly due to the advent of reliable techniques, enhancing the solution of an underdetermined system of equations under the assumption that the unknown data vector is sparse. These techniques consider not only, the theoretical quality of the signal processing, but also the numerical effort to achieve this quality. The inspiring studies of Donoho [1] and Tibshirani [2], leading to the Least Absolute Shrinkage and Selection Operator (LASSO), suggested to apply convex optimization to achieve numerical efficiency. Shortly after, many studies reported successful application of this technique to different practical problems, such as data acquisition [3], machine learning [4], parameter estimation [5, 6, 7]. Both the theoretical and implementation aspects of these applications have been studied carefully [8, 9].

The sparsity based approaches are suitable for the problems, where a good data model is available. Some recent studies addressed sparsity-based signal processing under model uncertainty or mismatch [10, 11]. More generally, recent investigations in this area considered learning, under the sparsity assumption, a separable model from a sequence of observations, and simultaneously estimating sparse vectors. The research is termed dictionary learning, and has received interest in research communities, where learning a model is an immediate concern [12, 13, 14, 15]. Image-based classification and machine learning are examples of such. However, dictionary learning rapidly extends its range to other problems, dealing with sparsity. The works, presented in [16, 17] are good examples in the recent literature. Dictionary learning has been significantly influenced by the invention of K-SVD, a numerically efficient learning technique [18]. Despite existence of multiple local minima, its successful application has been frequently reported. Few recent papers attempt to analyze the behavior of K-SVD. Still, the reason of its success is, to a great extent, unknown [19]. More importantly, the effect of noise is also currently neglected. Another observation is that K-SVD has a sharp performance transition, when its underlying assumptions are slightly violated. In this case, it is not clear, whether the process of learning can be enhanced by modifying the K-SVD, or the problem is fundamentally restricted.

We also observe a great potential in applying dictionary learning to a class of parametric estimation problems with separable models, where it is well-know that the size of a recoverable set of parameters is restricted by the size of the data set, observed at each time instant. Radar and sensor array-based estimation are good examples of such problems. As shown in Section 3.1, relying on mild sparsity assumptions, the dictionary learning techniques can remarkably improve this limit. Accordingly, we propose a research which considers the following issues

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- Adapting the dictionary learning setup to the parameter estimation case.
- The basic analysis of dictionary learning, leading to generic bounds on its performance.
- The analysis of the existing methods, such as K-SVD and comparison with the generic bounds.
- Based on the generic bounds, providing alternative learning solutions, under conditions, such as variable and/or unknown sparsity.

We discuss the topics above in more details in Section 4.

3 Survey

In this section, we present a brief introduction to the context of sparsity-based estimation and model learning, demonstrating basic ideas and techniques. For the interested reader, more specific references are provided in the text.

3.1 Sparsity-Based Estimation

Consider a problem, where an unknown vector $\mathbf{s}$ is to be estimated by observing a data vector $\mathbf{x}$, obtained by

$$\mathbf{x} = \mathbf{A}\mathbf{s} + \mathbf{n}, \tag{1}$$

where $\mathbf{n}$ is the observation noise and $\mathbf{A}$ is a known matrix, representing the relation between the observation $\mathbf{x}$ and the unknown variables $\mathbf{s}$. The simple relation in (1) underlies an enormous number of applications, and can be simply solved by the least square method, providing a statistically optimal result. Modern applications, however, demand a large size of the unknown parameters, while technological issues restrict the size of observation vector, leading to a situation, where the system of equations in (1) is underdetermined and hence (in the generic case) have infinite many solutions. On the other hand, the physical assumptions usually impose a strong structure on $\mathbf{s}$, which is essentially neglected in (1). Hence, a large body of research is devoted to incorporating data structure into the linear model in (1). A common case is where the vector $\mathbf{s}$ contains few non-zero elements. The position of the non-zero elements is unknown. Thus, the information in the data vector should amount for both the position and the value of nonzero elements. Hence, the required size of the observation vector is considerably smaller than the size of unknown vector $\mathbf{s}$. Solving (1) under the sparsity assumption is called sparsity-based estimation [8].

The sparsity based estimation has a long history, but has been recently brought into sharp focus. As a result, a number of powerful techniques, such as Orthogonal Matching Pursuit (OMP) [20], basis pursuit (BP) [1] and Sparsity Adaptive Matching Pursuit (SAMP) [21] has been recently developed. The main advantage of these techniques is that they guarantee a good performance with a reliable numerical technique. In particular, BP is shown to achieve the performance bound in the case of large random models $\mathbf{A}$, where it also enjoys numerical stability through convexity.

3.2 Sparsity-Based Model Learning

In many practical situations, the matrix $\mathbf{A}$ in (1) is either unknown, or partially known. Thus, it should be inferred along with the vector $\mathbf{s}$. This is only possible if a sequence of observations is provided as follows

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) \quad t = 1, 2, \ldots, T \tag{2}$$

Should there be an occasion to obtain the sequence $\{\mathbf{x}(t)\}$ from a known sequence $\{\mathbf{s}(t)\}$, the matrix $\mathbf{A}$ is simply obtained by solving a least square problem. In many applications, this is not the case, and the unknown vectors should be estimated together with the matrix $\mathbf{A}$ in a blind fashion.

The above problem of blind estimation is generally ill-posed. This means that the matrix $\mathbf{A}$ cannot be uniquely inferred from the sequence of observations. Similarly to Section 3.1, this may be resolved by imposing a structure on the unknown vectors $\{\mathbf{s}(t)\}$. In this context, the sparsity assumption has recently received considerable attention. It is often assumed that the vector $\mathbf{s}(t)$ has few nonzero elements at each time t, but the sparsity pattern (the position of the nonzero elements) vary by time, such that every column of $\mathbf{A}$ fairly often contributes to the observations. Then, it is expected that under some assumptions on the sparsity level (number of nonzero elements), the value of nonzero elements and the matrix $\mathbf{A}$, the model in (2) is uniquely resolved even if $\mathbf{A}$ is underdetermined (has less rows than columns). This is generally called the dictionary learning problem.

The previous research on dictionary learning has led to an iterative procedure, commonly considered in the recent literature [22, 23]. Each iteration starts by assuming the matrix, obtained from the previous iteration, and solving (2) for the unknown vectors $\mathbf{s}(t)$ by a suitable sparsity-based technique. The iteration is continued by assuming the sparsity pattern obtained from the sparsity based estimation, and simultaneously updating the matrix and the unknown nonzero entries of $\mathbf{s}(t)$. Performing the final step has been central in many recent research contributions. For example, the K-SVD approach proposes a cyclic approach to update the columns of $\mathbf{A}$ iteratively [18].

3.3 Parameter Estimation

In this section, we address the application of the framework, introduced in the prequel, to parameter estimation. We have previously studied the role of sparsity-based techniques in the parametric estimation problems.

Many problems, such as frequency and sensor array based estimation, including radar and sonar are related to a special type of model, referred to as separable. According to this model, the observed vector $\mathbf{x}$ is obtained by two sets of parameters $\{\theta_k\}$ and $\{s_k(t)\}$ known as positions and amplitudes, respectively. This is given by

$$\mathbf{x}(t) = \sum_{k=1}^{n} \mathbf{a}(\theta_k) s_k(t) + \mathbf{n}(t), \quad t = 1, 2, \ldots, T, \tag{3}$$

where $\mathbf{n}$ denotes the observation noise and $\mathbf{a}(\theta)$ is a vector-valued function of θ. Introducing $\mathbf{A} = [\mathbf{a}(\theta_1)\ \mathbf{a}(\theta_2), \ldots, \mathbf{a}(\theta_n)]$ and $\mathbf{s}(t) = [s_1(t)\ s_2(t) \ldots s_n(t)]^T$, the relation in (3) is commonly written as in (2). It is immediately seen that the parametric estimation problem is equivalent to model learning, introduced in Section 3.2, where the matrix $\mathbf{A}$ is restricted to be structured. We refer to this as parametric model learning. As seen, the parametric learning is subject to similar arguments to the general model learning problem, introduced in Section 3.2. For example, the identifiability of (3), in the absence of further assumptions on the amplitudes $\{s_k(t)\}$, is limited to the over determined matrices $\mathbf{A}$. However, we observe that according to the studies on dictionary learning, stated in Section 3.2, mild and realistic sparsity assumptions on the amplitude vector $\mathbf{s}(t)$ abandons this limitation. There are few recent studies on this topic, but a general analysis is lacking in the literature [13].

4 Proposed Project

The proposed project mainly focuses on the parametric model learning problem in (3), when a proper sparsity assumption on $\{s_k(t)\}$ is considered. Examples of such a model in practice are considered and discussed in Section 5. From a more technical point of view, this problem is the intersection of two lines of research; dictionary learning and parameter estimation. Accordingly, it is referred to as parametric dictionary learning. The result of the proposed project is useful in both areas of research, namely dictionary learning and parameter estimation. More specifically, we will consider the following issues, for some of which we have obtained some preliminary results.

4.1 Fundamental Bounds on Model Learning

In the study of any estimation problem, it is necessary to develop bounds on the best performance of the estimator, serving as a benchmark for a future analysis of specific estimation techniques. In the area of signal processing, these bounds are obtained by framing the desired problem statistically and using popular bounds such as Cramer-Rao and Chapman-Robinson inequalities, as well as Ziv-Zakai and Weiss-Weinstein bounds in the case of Bayesian estimation [24].

Consider the general model learning problem in Section 3.2. The statistical analysis is based on the notion of the likelihood function $p(\mathbf{x}(t) \mid \mathbf{A}, \mathbf{s}(t))$, as well as the estimator as a function $\hat{\mathbf{A}}(\{\mathbf{x}(t)\})$, assigning to any sequence of observations $\{\mathbf{x}(t)\}$ an estimate $\hat{\mathbf{A}}$ of the true model $\mathbf{A}$. The likelihood can be simply obtained by (2), or more elaborately by (3). Then, the general statistical results lead to expressions, imposing bounds on the precision of $\hat{\mathbf{A}}$. This is usually measured in terms of the error $\hat{\mathbf{A}} - \mathbf{A}$. However, the sparsity assumption complicates this approach. A more recent method is proposed in [25] to simplify the analysis in presence of sparsity.

In this project, we will consider the above statistical framework and examine both, the classical and the recent statistical results to obtain bounds on the estimation error. We aim to evaluate these bounds, at least in some asymptotic cases, such as a high SNR scenario, or the one with a large number T of observations. In particular, we will identify under which assumptions on the size and the structure of the matrix $\mathbf{A}$, together with the sparsity pattern in $\mathbf{s}(t)$, the asymptotic cases may lead to the true matrix $\hat{\mathbf{A}} = \mathbf{A}$.

4.2 The analysis of existing methods

To obtain a parametric dictionary learning, an existing method can be considered and adapted to the parametric setup. In particular, the parametric dictionary learning by K-SVD has recently gained attention. This project is aimed to provide an analysis for the application of K-SVD to the parametric problem, which at the same time, sheds light on the general behavior of K-SVD. The behavior of K-SVD is know to be difficult to analyze.

We perform the analysis in a statistical sense, where the model $\hat{\mathbf{A}} = \hat{\mathbf{A}}(\{\mathbf{x}(t)\})$, obtained by performing K-SVD is considered as an estimator. A typical analysis of an estimator usually assumes an asymptotic case, where it comprises of two stages. In the first stage, known as convergence analysis it is verified that $\hat{\mathbf{A}} = \hat{\mathbf{A}}(\{\mathbf{x}(t)\})$ converges to the true model $\mathbf{A}$ in (2) when the setup approaches to an ideal one. Then, the estimator is generally said to be consistent. Two popular ideal cases are obtained, when the noise term $\|\mathbf{n}(t)\|_2$ converges to zero and/or the sample size T grows to infinity. Our preliminary results show that K-SVD has a different behavior in the two ideal cases. In particular, we have discovered that it is consistent only in the noiseless case. In fact, we have identified a large class of inconsistent estimators, with the so-called joint-maximum-likelihood underlying structure.

In the second stage, the near ideal behavior of the estimate, under the consistency assumption, is analyzed. This is known as asymptotic error analysis, where, the mathematical tools of perturbation theory, such as Taylor expansion is commonly used to simplify the analysis. We have taken initial steps toward the error analysis of K-SVD, in an asymptotically low-noise $\mathbf{n}(t)$ setup.

4.3 New approaches

Along with the previous observations, our preliminary findings suggest that the K-SVD approach may not provide a statistically efficient result, in certain situations. High noise and variable sparsity are examples of such. Hence, we suggest alternative approaches. Here, the relation of the problem of interest to parameter estimation and machine learning provides a variety of different ideas. These ideas often lead an optimization expression. Emphasizing on the implementation aspects, the convexified approaches can be utilized to simplify the optimization procedure. Moreover, the statistical framework leads to a number of different nonlinear optimization procedures, which may suffer from local minima. Our analysis may also provide an occasion to introduce heuristic techniques. We introduce an interesting example in Section 6.3.

5 Significance

Signal processing under the model in (3) is exercised in a wide range of different applications, from data acquisition (sampling), sensor array signal processing and seismology to the financial and social sciences. Further assumption on the nature of the amplitudes is also widely common. Many signals such as speech and electroencephalogram (EEG) are well known to be sparse in certain domains. In the applications concerning these signals, the principle of sparsity has been widely used. However, parametric models are less discussed, due to their non-linear nature. Hence, the dictionary learning approach, especially in its parametric form is expected to have a huge impact on the future methods of diagnosis by EEG, speech coding algorithms and other disciplines, dealing with naturally sparse signals.

Another area of interest for the parametric dictionary learning is electromagnetic imaging. In applications, such as Synthetic Aperture Radar (SAR) and medical imaging, the sparse model in (3) is commonly valid. The sparsity, induced by the directionally selective behavior of the reflectors prolongs and degrades the process of obtaining a reliable image. In this case, the parametric dictionary learning approach will be highly useful. General radar and sonar systems may also benefit from the dictionary learning approach, especially in the long-range detection problems, where the combination of the scan process and the long range delay leads to the range ambiguity problem. In this case, viewing the model as a sparse separable one, the range ambiguity may be highly alleviated by the dictionary learning techniques. This is similar in nature to the frequency-domain aliasing effect by sampling a signal. From this perspective, the application of sparsity and dictionary learning is similar to the recent sparsity-based randomized sampling techniques [3].

The dictionary learning problem is directly connected to the well know blind source separation and blind deconvolution problems. In particular, it can be used for channel estimation in the wireless communication scenarios, where the channel estimation problem may be viewed as a blind separation problem. In this case, the parametric techniques promote faster and more reliable techniques than the current ones. Interestingly, the blind separation techniques also promote asynchronous communication in a multiuser wireless system, where synchronization and scheduling is widely used to cope with the intermittent data transmission and congestion. Considering the difficulties with synchronization and efficient scheduling in these scenarios, the sparsity based channel estimation by the dictionary learning techniques are expected to have a great impact on the quality of communication.

6 Preliminary Results

According to the research framework, posed in Section 4, we have discovered some preliminary results, identifying some key characteristics of the dictionary learning problem. In particular, we have shown that the K-SVD may not be consistent in presence of noise, while the general dictionary setup is identifiable under mild sparsity assumptions. We formulate these ideas in the sequel and present methods to overcome inconsistency.

6.1 General Bounds

We have considered the model in (3) and studied conditions, under which the model is consistent, i.e. the sequence of observations uniquely determines the parameters $\theta_1, \theta_2, \ldots, \theta_n$. In particular, we considered the large-sample-size case, where $T \to \infty$ as well as the low-noise case, where $\|\mathbf{n}(t)\|_2 \to 0$. The main findings are summerized below:

- Considering the case where $T \to \infty$, we have shown that the true parameters in (3) can be uniquely obtained under very mild conditions. Suppose that the amplitudes $s_k(t)$ are temporally independent and at every time instant t, the nonzero amplitudes, corresponding to the index set $I(t) = \{k \mid s_k(t) \neq 0\}$ are uncorrelated, centered and Gaussian-distributed. Define the collection $\mathcal{I} = \{I_1, I_2, \ldots, I_M\}$ of all index sets $I_k = I(t)$, occurring with a nonzero frequency and the $M \times n$ adjacency matrix $\mathbf{G} = (g_{i,j})$, where $g_{i,j} = 1$ if $i \in I_j$. Then, the model in (3) is identifiable if the matrix $\mathbf{G}$ has full column rank. In fact, this condition is surprisingly weak. Take an example, where the set $\mathcal{I}$ consists of all the index sets, missing exactly one index. This means that at every time, exactly one of the amplitudes is zero. Then, it is simple to see that the matrix $\mathbf{G}$ is not only of a full column rank, but also invertible, guaranteeing identifiability. Of course in this case, the model in (3) can remain highly underdetermined at each time instant.
- The situation is slightly different for the low-noise case where T is finite and fixed, and $\mathbf{n}(t) \to 0$ for every time $t = 1, 2, \ldots, T$. In this case, we can show that (3) is identifiable if in addition to the condition on the matrix $\mathbf{G}$, there exists for every index k an index set $I(t)$ such that $k \in I(t)$ and the model is over-determined (size of $I(t)$ is less than m).

6.2 Analysis of K-SVD

We also considered the convergence properties of the K-SVD method. It should be noted that K-SVD is an algorithm to solve the following optimization

$$\min_{\mathbf{A}, \{\mathbf{s}(t)\}} \sum_{t=1}^{T} \|\mathbf{x}(t) - \mathbf{A}\mathbf{s}(t)\|_2^2 \tag{4}$$

which we refer to as the Joint Maximum Likelihood (JML) estimator, as it jointly considers the ML principle for the model $\mathbf{A}$ and the amplitudes. Note that $\mathbf{s}(t)$ is assumed to be sparse.

The K-SVD algorithm locally solves the JML optimization. We discovered that the JML estimator is inconsistent in presence of noise and when $T \to \infty$. This means that the global minimum of (4) is different to the true model $\mathbf{A}$. Furthermore, the difference is proportional to the variance of the noise term $\mathbf{n}(t)$. Thus, JML is consistent for the low-noise case. However, the local optima should be further studied.

6.3 Alternative Approaches

The K-SVD approach suffers from local minima and is suitable, only when the order n and the number of nonzero amplitudes at each time is known and fixed. We present an alternative approach in the sequel. We are interested in studying this approach in more detail through this project.

In a parametric model learning problem such as (3), the JML optimization is solved over a structured dictionary $\mathbf{A}$, each column of which is given by $\mathbf{a}(\theta_k)$. Since the function $\mathbf{a}(\theta)$ is often nonlinear, ML leads to difficult optimization problems. It has been recently discovered that the sparsity-based estimation in Section 3.1 can be utilized to overcome the difficulty with the ML optimization. This is examined in an underdetermined case with non-sparse amplitudes. Here we generalize it to the parametric model learning case. We propose to consider a large (known) discretization $\tilde{\theta}_1, \tilde{\theta}_2, \ldots, \tilde{\theta}_N$ and calculate the matrix $\mathbf{A}_0 = [\mathbf{a}(\tilde{\theta}_1)\ \mathbf{a}(\tilde{\theta}_2) \ldots \mathbf{a}(\tilde{\theta}_N)]$. Then, the relation in (3) can be approximately written as

$$\mathbf{x}(t) = \mathbf{A}_0\tilde{\mathbf{s}}(t) + \mathbf{n}(t), \tag{5}$$

where $\tilde{\mathbf{s}} = [\tilde{s}_1(r), \tilde{s}_2(r), \ldots, \tilde{s}_N(r)]^T$ is a sparse vector. This is similar to (1), where $\mathbf{A}$ is replaced by $\mathbf{A}_0$. Thus, a sparsity-based technique can be applied to obtain $\tilde{\mathbf{s}}$. In particular, we propose to solve

$$\min_{\{\tilde{\mathbf{s}}(t)\}} \sum_{t=1}^{T} \|\mathbf{x}(t) - \mathbf{A}_0\tilde{\mathbf{s}}(t)\|_2^2 + \lambda \sum_{k=1}^{N} \sqrt{\sum_{t=1}^{T} |\tilde{s}_k(t)|^2} + \mu \sum_{k=1}^{N} \sum_{t=1}^{T} |\tilde{s}_k(t)|, \tag{6}$$

where $\lambda, \mu > 0$ control the order n and the average sparsity of the amplitudes, respectively; and should be properly chosen. Then, the position of the nonzero elements and their values give the estimates for the positions and amplitudes, respectively.

Previously, we have studied this technique when $\mu = 0$. We have developed methods to improve its implementation [26, 27, 28]. Since no specific assumption on the amplitudes $s_k(t)$ was made, the research was limited to the case, where $\mathbf{A} = [\mathbf{a}(\theta_1)\ \mathbf{a}(\theta_2), \ldots, \mathbf{a}(\theta_n)]$ was overdetermined. Generalization of this technique to the dynamic sparsity setup is also cinsidered [29].

7 Staffing, national and international collaboration

The proposed project will be conducted at the Signal Processing Group, Dept. of Signals and System, Chalmers. The research will be performed by post-doctoral researcher Ashkan Panahi under guidance by Prof. Tomas McKelvey. The project will also benefit from the other seniors in the group: Prof. Mats Viberg, Assoc. Prof. Lennart Svensson and Adjunct researcher Mikael Coldrey from Ericsson Research. The signal processing group has a long record in statistical signal processing and estimation and has well developed contacts in the area of sparse methods with Prof. Christoph Mecklembräuker at Technical University of Vienna and Prof. Babak Hassibi at California Institute of Technology. The proposed project will also complement the research performed on antenna systems in the Vinnova competence center CHASE (Chalmers Antenna Systems Excellence Center) hosted at our department.

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[17] S. Ravishankar and Y. Bresler, “Mr image reconstruction from highly undersampled k-space data by dictionary learning,” *Medical Imaging, IEEE Transactions on*, vol. 30, no. 5, pp. 1028–1041, 2011.

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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

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	Tomas McKelvey	20

Salaries including social fees

	Role in the project	Name	Percent of salary	2016	2017	Total
1	Other personnel with doctoral degree	Ashkan Panahi	100	718,000	743,000	1,461,000
2	Applicant	Tomas McKelvey	20	264,000	273,000	537,000
	Total			982,000	1,016,000	1,998,000

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	Total
1	Kontor	71,000	73,000	144,000
	Total	71,000	73,000	144,000

Running Costs

	Running Cost	Description	2016	2017	Total
1	Dator		20,000		20,000
2	Konferensresor		50,000	50,000	100,000
3	IT-stöd		22,000	22,000	44,000
	Total		92,000	72,000	164,000

Depreciation costs

Depreciation cost	Description	2016	2017

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	Total, applied	Other costs	Total cost
Salaries including social fees	982,000	1,016,000	1,998,000		1,998,000
Running costs	92,000	72,000	164,000		164,000
Depreciation costs			0		0
Premises	71,000	73,000	144,000		144,000
Subtotal	1,145,000	1,161,000	2,306,000	0	2,306,000
Indirect costs	360,000	373,000	733,000		733,000
Total project cost	1,505,000	1,534,000	3,039,000	0	3,039,000

Explanation of the proposed budget

Briefly justify each proposed cost in the stated budget.

Explanation of the proposed budget*

Besides the wage costs for the particiapating researchers the budget includes costs for premises (144 kkr), expense for a computer (20 kkr) and IT-services (44 kkr). During the project we plan to participate in 4 international conferences, each with a cost of 25 kkr (total 100 kkr) in order to disimminate the research results in the international community.

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

CV

March 26, 2015

Curriculum vitae: Professor Tomas McKelvey

Department of Signals and System
Chalmers University of Technology, SE-412 96 Göteborg
phone: +31 772 8061, fax: +46 31 772 1782
email: tomas.mckelvey@chalmers.se

1. **Higher education qualification:** 1991, Master of Science in Electrical Engineering (Civilingenjör, Elektroteknik), Lund Institute of Technology, Lund, Sweden.

2. **Doctoral degree:** 1995, Automatic Control, Linköping university, Linköping Sweden. Dissertation title: *Identification of State-Space Models from Time and Frequency Data.* Supervisor: Prof. Lennart Ljung.

3. **Postdoctoral positions:**

   January 1998 – March 1998: Postdoc visit at Department of Electrical Engineering, University of Newcastle, NSW, Australia

   July 1999 – July 2000: Postdoc visit at Department of Electrical Engineering, University of Newcastle, NSW, Australia

4. **Qualification required for appointments as a docent:** 1999, Automatic Control, April 20, 1999, Linköping university, Linköping Sweden

5. **Current Position:** From December 2006 Professor in Signal Processing, Department of Signals and Systems, Chalmers University of Technology, Sweden. 40% Research.

6. **Previous employments**

   June 1985 – July 1986: Software engineer, Cosab AB, Svalöv, Sweden

   1988 – 1991: Teaching assistant at the Department of Computer Science and Department of Information Theory, Lund Institute of Technology, Sweden

   Jan. 1990 – July 1990: Software engineer, Exomatic AB, Teckomatorp, Sweden

   June 1991 – Sept. 1991: Project employment at SAAB Military Aircraft AB, Linköping, Sweden

   Oct. 1991 – May 1995: PhD student, Automatic Control, Dept. of Electrical Engineering, Linköping University, Sweden

   June 1995 – Jan. 1997: Assistant Professor, Automatic Control, Dept. of Electrical Engineering, Linköping University, Sweden

   Feb. 1997 – June 2000: Associate Professor, Automatic Control, Dept. of Electrical Engineering, Linköping University, Sweden

   Aug. 2000 – Dec. 2006: Associate Professor (Docent), Signal processing, Dept. of Signals and Systems, Chalmers University of Technology, Göteborg, Sweden

8. **Supervision:**

   Ingemar Andersson (PhD main supervisor), 2005

   Joakim Gunnarsson (PhD main supervisor), 2007

   Per Sjövall (PhD co-supervisor), 2007

   Sima Shahsavari (PhD, main supervisor), 2011

Mikael Thor (PhD, co-supervisor), 2012

Markus Grahn, (PhD main supervisor) 2013

Ayca Ozcelikkale, (Post-Doc), 2014-15

9. Commissions of trust etc.

Oct. 1999 – present: Member of Program committee of IFAC Symposium on System Identification (SYSID), a triennial conference.

Jan. 2000 – July 2002: Vice-Chairman of International Federation of Automatic Control's (IFAC) Technical Committee on Modelling, Identification and Signal Processing.

Sept. 2001 – Nov. 2002: Member of Chalmers education committee for Electrical Engineering undergraduate studies. (Linjekommitte E)

March 2002 – March 2005: Associate editor for Automatica, a Journal of the International Federation of Automatic Control.

July 2002 – July 2005: Chair of the International Federation of Automatic Control's (IFAC) Technical Committee on Modelling, Identification and Signal Processing.

July 2004 – July 2005: Member of program committee of the 16th IFAC World Congress 2005.

Oct. 2002 – present: Member of the international review committee of the VOLVO Car Corporation industrial Ph.D. program (VIPP).

Jan. 2005 – Sep. 2011: Vice head of Department undergraduate education (Viceprefekt med ansvar för grundutbildningen), Department of Signals and Systems, Chalmers University of Technology, Sweden

March 2006 – Jan. 2015: Associate editor for Journal of Control Science and Engineering.

Jan. 2008 – Dec. 2010: Member of the Chalmers board for undergraduate education (GUN).

Jan. 2008 – Dec. 2010: Vice chair of the Chalmers committee for quality assurance in undergraduate education.

Sept. 2011– present: Member of the steering group of "Stroke Centrum Väst" at Sahlgrenska Akademin, Göteborgs Universitet.

Jan. 2012 – present: Member of Executive Board of CHASE, (Chalmers Antenna Systems, a VINN Excellence Center)

Sept. 2012 – present: Member of the advisory board of the Electrical Engineering undergraduate program, Chalmers.

Jan 2014 – present:. Member of the board for Combustion Engine Research Center (CERC) at Chalmers.

From April 2011: Head of Signal Processing group.

From Jan 2014: Head of Signal Processing group including responsibilities for personnel.

From Jan 2015: Vice head of department of Signals and Systems (Pro-prefekt)

Publication list

Publications by Tomas McKelvey

Google Scholar database has been used as source for number of citations.

Peer-reviewed original articles

[1] I Andersson, T McKelvey, and M Thor. Evaluation of torque sensor based cylinder balancing in an si engine. *SAE Int. J. Passeng. Cars - Electron.Electr.Syst*, 1(1):365–371, 2008. Number of citations:-.

[2] S. Borguet, M. Henriksson, T. McKelvey, and O. Léonard. A study on engine health monitoring in the frequency domain. *Journal of Engineering for Gas Turbines and Power*, 133(8):081604, 2011. Number of citations:3.

[3] S. Shahsavari, T. McKelvey, C. E. Ritzen, and B. Rydenhag. Cerebrovascular mechanical properties and slow waves of intracranial pressure in tbi patients. *IEEE Transactions on Biomedical Engineering*, 58(7):2072–2082, 2011. Number of citations:3.

[4] I. Andersson, M. Thor, and T. McKelvey. The torque ratio concept for combustion monitoring of internal combustion engines. *Control Engineering Practice*, 2012. Number of citations:3.

[5] Y. Yu, J. Yang, T. McKelvey, and B. Stoew. Compact uwb indoor and through-wall radar with precise ranging and tracking. *International Journal of Antennas and Propagation*, 2012. Number of citations:9.

[6] T. Bengtsson, T. McKelvey, and I. Y.-H. Gu. Super-resolution reconstruction of high dynamic range images in a perceptually uniform domain. *SPIE, Journal of Optical Engineerng*, 52(10), May 2013. Number of citations:1.

[7] Markus Grahn, Krister Johansson, and Tomas McKelvey. Data-driven emission model structures for diesel engine management system development. *International Journal of Engine Research*, page 1468087413512308, 2014. Number of citations:-.

[8] Mikael Thor, Bo Egardt, Tomas McKelvey, and Ingemar Andersson. Using combustion net torque for estimation of combustion properties from measurements of crankshaft torque. *Control Engineering Practice*, 26:233–244, 2014. Number of citations:-.

[9] Tim Howells, Ulf Johnson, Tomas McKelvey, and Per Enblad. An optimal frequency range for assessing the pressure reactivity index in patients with traumatic brain injury. *Journal of clinical monitoring and computing*, 2014. DOI:10.1007/s10877-014-9573-7, Number of citations:1.

[10] Markus Grahn, Krister Johansson, and Tomas McKelvey. Model-based diesel engine management system optimization for transient engine operation. *Control Engineering Practice*, 29(0):103 – 114, 2014. Number of citations:-.

[11] Johan Nohlert, Livia Cerullo, Johan Winges, Thomas Rylander, Tomas McKelvey, A. Holmgren, Lubomir Gradinarsky, Staffan Folestad, Mats Viberg, and Anders Rasmuson. Global monitoring of fluidized-bed processes by means of microwave cavity resonances. *Measurement: Journal of the International Measurement Confederation*, 55:520–535, 2014. Number of citations:-.

[12] M. Persson, A Fhager, H. Trefna, Y. Yu, T. McKelvey, G. Pegenius, Jan-Erik Karlsson, and M. Elam. Microwave-based stroke diagnosis making global pre-hospital thrombolytic treatment possible. *Biomedical Engineering, IEEE Transactions on*, PP(99):1–1, 2014. Number of citations:7.

[13] Mikael Thor, Bo Egardt, Tomas McKelvey, and Ingemar Andersson. Closed-loop diesel engine combustion phasing control based on crankshaft torque measurements. *Control Engineering Practice*, 33:115–124, 2014. Number of citations:-.

[14] Yinan Yu and Tomas McKelvey. A robust subspace classification scheme based on empirical intersection removal and sparse approximation. *Integrated Computer-Aided Engineering*, 22:59–69, 2015. Number of citations:-.

Peer-reviewed conference contributions

[1] J. Gunnarsson and T. McKelvey. Reducing noise sensitivity in F-ESPRIT using weighting matrices. In *Proc. 15th European Signal Processing Conference*, pages 783–787, Poznan, Poland, Sept. 2007. EUSIPCO. Number of citations: 1.

[2] S. Shasavari, T. McKelvey, T. Skoglund, and C. Eriksson-Ritzen. Transfer function of arterial blood pressure to intracranial pressure and its relationship to index of compensatory reserve in traumatic brain injury. In *Proc. 13th International Symposium on Intracranial Pressure and Brain Monitoring*, San Francisco, CA, July 2007. Number of citations:-.

[3] T. McKelvey, I. Andersson, and M. Thor. Estimation of combustion information by crankshaft torque sensing in an internal combustion engine. In *Proc. The Second International Workshop on Computational Advances in Multi-Sensor Adaptive Processing*, St. Thomas, VI, USA, Dec 2007. Number of citations:-.

[4] P. Sjövall, T. Abrahamsson, and T. McKelvey. Indirect vibration sensing and optimal sensor placement. In *Proc. 26th International Modal Analysis Conference (IMAC-XXVI)*, Orlando, FL., Feb 2008. Number of citations: 2.

[5] T. McKelvey, H. Atatla, and D.O. Blanco Parada. A subspace method for frequency selective identification of stochastic systems. In *In proc. 17th IFAC World Congress*, pages 8846–8851, Seoul, Korea, July 2008. IFAC. Number of citations: 3.

[6] S. Shahsavari and T. McKelvey. Harmonics tracking of intracranial and arterial blood pressure. In *Proc. of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2008. Number of citations: 1.

[7] S. Shahsavari and T. McKelvey. Frequency interpretation of tidal peak in intracranial pressure wave. In *Proc. of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2008. Number of citations: 1.

[8] M. Thor, I. Andersson, and T. McKelvey. Parameterized diesel engine heat release modeling for combustion phasing analysis. In *Proc. SAE 2009 World Congress*, pages Paper 2009–01–0368, April 2009. Number of citations: 1.

[9] M. Thor, I. Andersson, and T. McKelvey. Modeling, identification, and separation of crankshaft dynamics in a light-duty diesel engine. In *SAE Technical Paper Series 2009-01-1798, SAE 2009 International Powertrains, Fuels & Lubricants Meeting*, page 95175, 2009. Number of citations: 1.

[10] S. Shahsavari, T. Hallen, T. McKelvey, C Eriksson-Ritzen, and B. Rydenhag. Normalized power transmission between ABP and ICP in TBI. In *Proceedings of the 31st Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society*, pages 4699–4703, Minneapolis, MI, 2009. Number of citations:-.

[11] M. Thor, I. Andersson, and T. McKelvey. Estimation of diesel engine combustion phasing from crankshaft torque data. In *IFAC Workshop on Engine and Powertrain Control, Simulation and Modeling, Paris, France*, page 102854, 2009. Number of citations: 2.

[12] M.A. Khorshidi, T. McKelvey, M. Persson, and H. Dobsicek Trefna. Classification of microwave scattering data based on a subspace distance with application to detection of bleeding stroke. In *The Third International Workshop on Computational Advances in Multi-Sensor Adaptive Processing*, Aruba, Dutch Antilles, Dec. 2009. Number of citations: 5.

[13] S. Borguet, M. Henriksson, McKelvey T., and O. Leonard. A study on engine health monitoring in the frequency domain. In *Proceedings of ASME Turbo Expo 2010: Power for Land, Sea and Air*, Glasgow, UK, 2010. Number of citations:-3.

[14] A. Fhager, T. McKelvey, and M. Persson. Stroke detection using a broad band microwave antenna system. In *EUCAP2010, 4th European Conference on Antennas and Propagation, April 12-16, Barcelona, Spain. s. C13P1-2*, 2010. Number of citations: 5.

[15] P. Löwhagen, S. Söndergaard, B. Rydenhag, T. McKelvey, C. Eriksson-Ritzen, and A. Åneman. Baroreceptor sensitivity and heart rate variability in early traumatic brain injury. In *Intensive Care Medicine*, volume 36, page S185. 23rd ESICM ANNUAL CONGRESS, BARCELONA, SPAIN 9-13 OCTOBER 2010, 2010. Number of citations:-.

[16] S. Shahsavari, T. McKelvey, B. Rydenhag, and C. Eriksson-Ritzen. Pulse wave velocity in patients with severe head injury: A pilot study. In *Proc. of the 32nd Annual International Conference of the IEEE. Engineering in Medicine and Biology Society.*, pages 5277–5281, 2010. Number of citations: 1.

[17] S. Shahsavari, T. McKelvey, B. Rydenhag, and C. Eriksson-Ritzen. Plateau waves and baroreflex sensitivity in patients with head injury: A case study. In *Proceedings of the 33rd Annual International Conference of the IEEE. Engineering in Medicine and Biology Society.*, Boston, MA, 2011. Number of citations: 1.

[18] M. Thor, B. Egardt, T. McKelvey, and I. Andersson. Estimation of combustion phasing using the combustion net torque method. In *Proceedings of the 18th IFAC World Congress*, pages 11827–11832, Milano, Italy, 2011. Number of citations: 1.

[19] M. Grahn, J-O. Olsson, and T. McKelvey. A diesel engine model for dynamic drive cycle simulations. In *Proceedings of the 18th IFAC World Congress*, pages 11833–11838, Milano, Italy, 2011. Number of citations: 1.

[20] S.H. Yousefi Mesri, M. Khazaeli Najafabadi, and T. McKelvey. A multidimensional signal processing approach for classification of microwave measurements with application to stroke type diagnosis. In *33rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Boston, MA, 2011. Number of citations: 2.

[21] Y. Yu, S. Maalik, J. Yang, T. McKelvey, K. Malmstrm, L Landn, and B. Stoew. A new uwb radar system using uwb cmos chip. In *Proceedings of the 5th European Conference on Antennas and Propagation, EUCAP 2011*, pages 771–775, Rome, Italy, 2011. Number of citations:-.

[22] M. Persson, T. McKelvey, A. Fhager, H. Lui, Y. Shirvany, A. Chodoroski, Q. Mahmood, F. Edelevik, M. Thordstein, A. Hedström, and M. Elam. Advances in neuro diagnostic based on microwave technology, transcranial magnetic stimulation and eeg source localization. In *Asia Pacific Microwave Conference*, Melbourne, Australia, 2011. Number of citations:-.

[23] M. Grahn, K. Johansson, K. Vartia, and T. McKelvey. A structure and calibration method for data-driven modeling of nox and soot emissions from a diesel engine. In *Proc. SAE 2012 World Congress*, pages 2012–01–0355, April 2012. Number of citations: 4.

[24] M Thor, B Egardt, T. McKelvey, and I Andersson. Parameterized diesel engine combustion modeling for torque based combustion property estimation. In *Proc. SAE 2012 World Congress*, pages 2012–01–0907, April 2012. Number of citations:-.

[25] T McKelvey and G. Guerin. Non-parametric frequency response estimation using a local rational model. In *Proc. 16th IFAC Symposium on System Identification*, Brussels, Belgium, 2012. IFAC. Number of citations: 10.

[26] Y. Yu, J Winges, T. McKelvey, and Rylander T. Model reduction for inverse scattering problems. In *AntennEMB*, Stockholm, March 2012. Number of citations:-.

[27] Y. Yu, T. Yang, J. ad McKelvey, and et al. Development of a compact uwb radar system for indoor ranging and tracking. In *COST IC1102, 2nd WG Meeting & Technical Workshop*, Istanbul, Sep. 2012. Number of citations:-.

[28] Y. Yu and T. McKelvey. A subspace learning algorithm for microwave scattering signal classification with application to wood quality assessment. In *IEEE International Workshop on Machine Learning for Signal Processing (MLSP)*, 2012. Number of citations: 1.

[29] J. Yang, A. Kishk, A. Razavi, Y. Yu, T. McKelvey, B. Stoew, S. Abtahi, S. Kidborg, and A. Al-Rawi. The new uwb self-grounded bow-tie antennas and the applications in different systems. In *Swedish Radio and Microwave Days 2012, RVK2012*, Stockholm, 2012. Number of citations:-.

[30] J. Yang, J. Yin, M. Pantaleev, Y. Yu, T. McKelvey, S. Fayazi, and H.S. Lui. Several new ultra-wideband antenna systems for radio telescopes and industry sensor imaging process. In *14th International Conference on Electromagnetics in Advanced Applications, ICEAA*, pages 1281–1284, Cape-Town, Sept. 2012. Number of citations: 1.

[31] M. Grahn, K. Johansson, and T. McKelvey. B-splines for diesel engine emission modeling. In *IFAC Workshop on Engine and Powertrain Control, Simulation and Modeling*, pages 416–423, Rueil-Malmaison, Oct. 2012. Number of citations:-.

[32] S. Candefjord, A.A. Malik, S. Kidborg, Y. Yu, T McKelvey, A. Fhager, and M. Persson. Using microwave technology for detecting traumatic intracranial bleedings - tests on a brain phantom. In *Medicinteknikdagarna*, 2012. Number of citations:-.

[33] S. Candefjord, A.M. Ahmad, S. Kidborg, Y. Yu, T. McKelvey, A. Fhager, and M. Persson. Microwave technology shows potential for detecting traumatic intracranial bleedings. In *Proc. 7th European Conference on Antennas and Propagation*, 2013. Number of citations:-.

[34] A. Razavi, J. Yang, and T. McKelvey. Optimal aperture distribution of near-field antennas for maximum signal penetration. In *Proc. 7th European Conference on Antennas and Propagation*, 2013. Number of citations:-.

[35] A. Fhager, Yinan. Yu, T. McKelvey, and M. Persson. Stroke diagnostics with a microwave helmet. In *Proc. 7th European Conference on Antennas and Propagation*, 2013. Number of citations: 5.

[36] M. Persson, A. Fhager, H. Dobsicek Trefna, and T. McKelvey. Microwave based diagnostics and treatment. In *Proc. 7th European Conference on Antennas and Propagation*, 2013. Number of citations: 2.

[37] L. Cerullo, J. Nohlert, J. Winges, T. Rylander, L. Gradinarsky, M. Viberg, and S. Folestad. Microwave measurements for metal vessels. In *Proc. 7th European Conference on Antennas and Propagation*, 2013. Number of citations:-.

[38] T. Bengtsson, T. McKelvey, and I.Y.-H. Gu. Super-resolution reconstruction of high dynamic range images with perceptual weighting of errors. In *Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2013. Number of citations:-.

[39] Y. Yu, T. McKelvey, and Kung S.-Y. A classification scheme for high-dimensional-small-sample-size data using SODA and ridge-SVM with microwave measurement applications. In *Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2013. Number of citations:-.

[40] S. Candefjord, J. Winges, Y. Yu, and T. McKelvey. Microwave technology for localization of traumatic intracranial bleedings-A numerical simulation study. In *Proc. 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'13)*, July 2013. Number of citations:-.

[41] M. Grahn, K. Johansson, and T. McKelvey. An optimization strategy for diesel engine management systems. In *7th IFAC Symposium on Advances in Automotive Control*, Sept. 2013. Number of citations:-.

[42] Y. Yu and T. McKelvey. A unified subspace classification framework developed for diagnostic system using microwave signal. In *Proc. of 21st European Signal Processing Conference (EUSIPCO)*, Marrakech, Marocco, Sept. 2013. EURASIP. Number of citations:1.

[43] Y. Yu, T. Diamantaras, K. I. ; McKelvey, and et.al. Ridge-adjusted slack variable optimization for supervised classification. In *Proc. IEEE International Workshop on Machine Learning for Signal Processing*, Southampton, UK, Sept. 2013. Number of citations:1.

[44] Y. Yu, T. McKelvey, and S Kung. Kernel soda: A feature reduction technique using kernel based analysis. In *Proc. 12th International Conference on Machine Learning and Applications (ICMLA'13)*, Miami, Florida, Dec. 2013. Number of citations:-.

[45] Yinan Yu, Tomas McKelvey, and S.Y. Kung. Feature reduction based on sum-of-snr (sosnr) optimization. In *The 39th IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, pages 6756–6760, 2014. Number of citations:-.

[46] Johan Winges, Livia Cerullo, Thomas Rylander, Tomas McKelvey, Lubomir Gradinarsky, Stafan Folestad, and Mats Viberg. A microwave measurement system for measurement of dielectric properties. In *AntennEMB, 11-12 March, Gteborg*, 2014. Number of citations:-.

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[1] S. Shahsavari, T. McKelvey, T. Skoglund, and C. Eriksson Ritzen. A comparison between the transfer function of ABP to ICP and compensatory reserve index in TBI. In Manley, Hemphill, and Stiver, editors, *Intracranial Pressure and Brain Monitoring XIII - Mechanisms and Treatment*, number 102 in Acta Neurochirurgica Supplementum, pages 9–13. Springer, 2009. Number of citations:-.

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[1] T. McKelvey, H. Akçay, and L. Ljung. Subspace-based multivariable system identification from frequency response data. *IEEE Trans. on Automatic Control*, 41(7):960–979, July 1996. Number of citations: 330.

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CV

Name: Tomas McKelvey	**Doctorial degree:** 1995-05-05
Birthdate: 19660407	**Academic title:** Professor
Gender: Male	**Employer:** Chalmers tekniska högskola

Research education

Dissertation title (swe)
Identifiering av tillståndsmodeller from tid- och frekvensdata

Dissertation title (en)
Identification of State-Space Models from Time and Frequency Data

Organisation	Unit	Supervisor
Linköpings universitet, Sweden Sweden - Higher education Institutes	Institutionen för systemteknik (ISY)	Lennart Ljung

Subject doctors degree	ISSN/ISBN-number	Date doctoral exam
20202. Reglerteknik	ISBN:91-7871-531-8 ISSN:0345-7524	1995-05-05

Publications

Name: Tomas McKelvey	**Doctorial degree:** 1995-05-05
Birthdate: 19660407	**Academic title:** Professor
Gender: Male	**Employer:** Chalmers tekniska högskola

McKelvey, Tomas 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.