Application

2015-03-31

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Information about applicant

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Year:	2016	2017	2018	2019
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Descriptive data

Project info

Project title (Swedish)*

Gles signalbehandling över nätverk och grafer

Project title (English)*

Sparse processing over networks and graphs

Abstract (English)*

In line with the long term vision of engineering technologies for big data analysis, a grand challenge is how existing signal processing and machine learning concepts and methodologies can be extended to facilitate analysis of large-dimensional signals/data on networks/graphs. Such networked signals/data are in abundance today, for example in application scenarios of social and economic networks, epidemiology, biological networks, transportation networks, Internet blog data, recommendation systems, etc. To use network connectivity information in big data analysis, recent efforts in signal processing and machine learning have led to the emergence of the notion of signal processing on graphs and learning over networks. Further, in the last decade, sparse processing has been proven to have high potentials for many applications. The area of sparse processing is still growing at a high pace. The overwhelming success of sparse processing methodologies – such as compressed sensing, sparse representations, dictionary learning – is due to the fact that sparsity is a key concept in nature and its presence is ubiquitous.

The Sparse processing Over Networks and Graphs (SparseNet) project is to address the grand challenge of extending sparse processing technologies to the new concepts of signal processing on graphs and learning over networks. The purpose of SparseNet is to investigate the fundamental question: how graph/network aspects affect performance of a large-scale networked system that comprises of nodes performing large-dimensional sparse processing tasks. A primary example of such system is a wireless sensor network where sensors use compressed sensing technologies. The engineering aims of developing new novel theoretical frameworks and algorithmic means for sparse processing over graphs/networks will be achieved by using inter-disciplinary nature of scientific methods from distributed optimization, statistical signal processing, machine learning, statistical physics, and coding. The SparseNet project has a high relevance for the societal challenges of health, security, commerce, transport and climate monitoring, and the scientific significance lies in the scope of developing new fundamental theoretical problems with foundational aspects.

Popular scientific description (Swedish)*

'Data Deluge' ('Störtfloden av data') och 'Big Data' är två nya termer som idag ofta förekommer i nyheterna. Med vad betyder termerna? Svaret är att människor och maskiner idag genererar stora mängder data i vår uppkopplade värld. Avläsningar av strömförbrukning, data från parkeringsautomater, trafikdata, meteorologisk data, sociala nätverk, rekommendationssystem, patientjournaler, genetisk data, bloggar, tweets på twitter, email och många andra exempel finns på hur stora mängder data genereras, precis som en störtflod av data. Detta kallas Big Data. Störtfloden av data skapar många nya möjligheter till att analysera data och utvinna viktig information som inte var möjliga för några år sedan när datamängderna var betydligt mindre. Vidare har nästan all data vissa grundläggande egenskaper, den är sammankopplad via ett nätverk eller har en grafstruktur, som kommunikationen i sociala nätverk eller produktrekommendationer på internet.

Frågan uppstår: hur kan vi hantera så stora datamängder? Till exempel överstiger alla avläsningar av strömförbrukningen utrymmet på hårddiskarna i ett datacenter. Hur kan vi analysera strömförbrukningen för att analysera hur kundernas beteende påverkar elförbrukningen? Det är naturligt att använda den gleshet som existerar i många naturliga datamängder som genereras av människor och maskiner. Gleshet finns överallt – på natthimlen finns stjärnor, men de tar bara upp en bråkdel av natthimlen. Det betyder att större delen av natthimlen inte innehåller någon information. Nästan all data är typiskt gles och det exiterar metoder som kan utnyttja glesheten för att utvinna information, men det exiterar nästan inga metoder som utnyttjar gleshet för stora datamängder i nätverk och grafer. Projektet SparseNet har som syfte att utveckla nya metoder för att hantera stora datamängder i nätverk och grafer, det kommer därför vara ett betydelsefullt steg i analysen av stora datamängder. Notera att de viktigaste aspekterna för att bättre kunna utvinna information från stora datamängder är gleshet, nätverk och grafer.

Project period

Number of project years*

4

Calculated project time*

2016-01-01 - 2019-12-31

Deductible time

Deductible time

Cause	Months
Career age: 72	

Career age is a description of the time from your first doctoral degree until the last day of the call. Your career age change if you have deductible time. Your career age is shown in months. For some calls there are restrictions in the career age.

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

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

Keyword 1*

Sparse signal processing

Keyword 2*

Compressed sensing

Keyword 3*

Machine learning

Keyword 4

Graphs

Keyword 5

Networks

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*

We hope that no question will arise on the ground of ethics for this project proposal. No research will be performed on humans or animals. We will also not deal with any personal information.

The project includes handling of personal data

No

The project includes animal experiments

No

Account of experiments on humans

No

Research plan

Sparse Processing Over Networks and Graphs (SparseNet)

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March 30, 2015

Research Proposal for the Call
Project Research Grant for Junior Researcher
Natural and Engineering Sciences

Vetenskapsrådet (VR) 2015
by Dr. Saikat Chatterjee, KTH

References: References are provided in two different places. References with usual appearance are provided in the end of this Research Plan, and the references with an initial "SC" are provided in the Publication List of the project applicant 'Saikat Chatterjee').

A.1 Ethical Considerations

We hope that no question will arise on the ground of ethics for this project proposal. No research will be performed on humans or animals. We will also not deal with any personal information.

A.2 Purpose and Aims

A modern **long term vision** is to engineer signal processing and machine learning algorithms for large-dimensional signals/data (**big data**). The vision has generated significant interests and opportunities in recent times, thanks to the data deluge experienced by an increasing number of scientific disciplines. Advances in smart device and networked applications have resulted in an increased dimensionality and diversity of generated data, posing new challenges in the analysis of large-dimensional data, particularly, in presence of their **networked or connected nature**.

Naturally a **grand challenge** is: how existing signal processing and machine learning concepts and methodologies may be extended to facilitate our understanding of such data, while making use of the **network connectivity information**.

To use network connectivity information, recent efforts in signal processing and machine learning have led to the emergence of the notion of **signal processing on graphs** [A7, A1] and **learning over networks** [A2] where signals/data exist on nodes of a graph/network. For a practical example, in weather prediction, weather data of Swedish cities can be modeled via a network graph; the graph nodes are the cities and the graph links may be parameterized by a function of physical distances between cities and difference of longitudes and latitudes of cities. In another example, for a large scale wireless sensor system, the communication network between sensors represent the network graph. Many examples can be drawn for signals/data on graphs/networks in application scenarios of social and economic networks, epidemiology, biological networks, transportation networks, Internet blog data, recommendation systems, etc.

On the other hand, use of sparsity in signal processing and machine learning – referred to as **sparse processing** – is found to have high success for many applications in wide field of information and communication technologies (ICT). Research activities in sparse processing is growing, thanks to immense opportunities in various applications. Sparse processing tools – such as compressed sensing, sparse representations, low-rank matrix sensing, dictionary learning – are relatively **mature** technologies providing high potential to measure, process and analyze **large-dimensional** signals/data. Along-with traditional ℓ_2-norm based optimizations (for example, least squares based estimations), the use of sparsity promoting ℓ_1-norm based optimization has become a standard practice. Sparse processing is even proved to be useful for large-scale biological data analysis where we also recently contributed [SC18]. The special mention of biological data analysis is not a digression here because there exists the wide spread **belief** that the first half of the 21st century will belong to biology and has a true essence of high level complexity in big data analysis. Typically the *signal processing on graph*, *learning over network* and *sparse processing* are treated as **separate areas** so far and there is no tangible research effort in horizon to investigate them either in a unified framework or by cross-exchanging ideas and concepts. This lack of research effort translates to a **significant void** in pursuit of the grand challenge.

The Sparse processing Over Networks and Graphs (SparseNet) project is to address the **grand challenge of extending sparse processing technologies to the new concepts of signal processing on graphs and learning over networks**.

The **purpose** of SparseNet is to investigate the **fundamental question**: *how graph/network aspects affect performance of a large-scale networked system that comprises of nodes performing large-dimensional sparse processing tasks? Further what happens to the system if the graph/network is sparse by nature or due to engineering requirement?* A primary example of such system is a wireless sensor network where sensors use compressed sensing and low-rank matrix sensing technologies. A sparse graph/network is useful to model either communication resource constrained scenarios for wireless sensor network, or non-uniform interaction between nodes that arise naturally in biological networks and social networks. Non-uniform interaction naturally arises in many applications, for example, in social network where a user often communicates with a small number of users from the set of all connected users. *For bringing synergy between network/graph aspects and state-of-the-art sparse processing systems,* ***the technical goal*** *of* SparseNet *is to construct new signal models and engineer novel algorithms with good theoretical insights*. The purpose of SparseNet project has a **high relevance for the societal challenges** of health, security, commerce, transport and climate monitoring.

In SparseNet, **important natural questions** are: (1) how the graph/network structure (topology) and communication aspects affect sparse processing performance? (2) what is the trade-off between resources for sparse processing and resources for graph/network to achieve optimal resource allocation? For example, in a camera sensor network for surveillance, how to trade-off between resolution of cameras, number of cameras and number of network links to connect the cameras? (3) how robust is the sparse processing performance in presence of deteriorating network quality, such as network link failures? To answer the questions, the **engineering aims** of SparseNet project are to:

1. develop theoretical frameworks for using sparse processing over graphs/networks;
2. develop novel algorithms and their performance analysis over network topologies;
3. characterize robust sparse processing performance with imperfect network links;
4. validate design solutions through simulations, real data and a testbed camera network platform.

Using methods from statistical physics, distributed optimization, statistical signal processing, machine learning, and coding, the SparseNet project expects impactful progress in designing new practical schemes and theoretical analysis. **This will make a significant step towards the long term vision**.

A.3 Survey of the field

In this section we provide necessary background on sparse processing, signal processing on graphs and learning over networks, followed by mentioning important missing aspects and our related endeavour.

Sparse Processing

In standard sparse processing – such as compressed sensing, sparse representations, low-rank matrix sensing, dictionary learning – we typically consider underdetermined setups and use the existence of sparsity in natural and man-made signals/data as a regularization factor. For **compressed sensing** (CS), a sparse signal $\mathbf{x} \in \mathbb{C}^{N\times 1}$ is sensed in a linear manner using the measurement matrix $\mathbf{A} \in \mathbb{C}^{M\times N}$ modeling a CS sensor, and the measurement vector is

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{w} \in \mathbb{C}^{M\times 1}, \tag{1}$$

where $\mathbf{w}$ be measurement noise and $M \ll N$. The aspect $M \ll N$ provides the scope of measuring large-dimensional source $\mathbf{x}$ by low-dimensional measurement $\mathbf{y}$, and hence holds high potential for big data applications. Note that (1) is under-determined (or under-sampled) that can be represented by $\rho = \frac{M}{N} \in (0, 1]$. A low ρ is preferable because it corresponds to a reduction in measurements. The signal $\mathbf{x}$ is assumed to be sparse directly in the canonical Euclidean basis or in a sparsity promoting transform (known as dictionary). The setup (1) not only considers CS, but encompasses variety of sparse processing methods. For example, in **low-rank matrix sensing** (LRMS), $\mathbf{x}$ is a vectorized form of a low-rank matrix (a low-rank matrix is sparse in singular values). In **sparse representations**, $\mathbf{y}$ represents a signal and we find its sparse representation $\mathbf{x}$ in a known dictionary denoted by $\mathbf{A}$. For **dictionary learning**, the dictionary $\mathbf{A}$ can be learned from data, or comprised of fixed deterministic transforms promoting sparse representation. Sparse representations and dictionary learning are well connected with the engineering field of data compression (or source coding). Examples of transforms that can form a deterministic dictionary by concatenation are discrete wavelet transform (DWT), discrete cosine transform (DCT), discrete Fourier transform (DFT), etc. Naturally the setup (1) is quite general in the gamut of sparse processing. *Finally we mention that sparsity is used for sparse filtering, sparse power spectrum estimation, sparse linear prediction, sparse regression, sparse Bayesian learning, sparse kernel machines, and many other signal processing and machine learning schemes*. The **overwhelming success** is due to the fact that **sparsity is a key concept in nature**, and its presence is **ubiquitous**.

Concentrating on CS setup (1), a large body of work addressed the issue of reconstructing $\mathbf{x}$ from $\mathbf{y}$, and theoretical analysis of the reconstruction performance. Typical reconstruction algorithms are based on convex optimization (ℓ_1-norm minimization), iterative greedy search (algebraic signal processing), and Bayesian machine learning (finding a posterior given sparsity promoting prior). Popular theoretical analysis tools are mainly **worst case** approaches, such as using *mutual coherence* [A3] and *restricted isometry property* (RIP) of sensing matrices [A4]. Very **recently**, tools from the field of **statistical physics** are applied to characterize **average performance measure**. The tool is called **replica method** which is widely used to study the *mean field spin glasses* in the *condensed matter physics* [A5]. An example of using replica method in CS is [A6]. So far there is no work on analyzing average performance of LRMS.

Signal Processing on Graphs

A number of concepts from standard discrete-time signal processing (DSP) have been recently extended to the new paradigm called signal processing on graphs [A7, A1], and it is shown to have a considerable potential for big data analysis [A8]. Let $G = (\mathcal{V}, \mathcal{E})$ is a **graph** where $\mathcal{V} = \{1, 2, \ldots, K\}$ is the set of K nodes and $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$ is the set of edges between pair-wise nodes. Suppose $\mathbf{x} \in \mathbb{R}^N$ be a real signal on the graph G. Now we show how the **graph Fourier transform** (GFT) is defined as an example of extending signal processing ideas for signals on graph. Assuming $\mathbf{M}$ denotes the adjacency matrix of the graph G, the GFT $\mathcal{F}_g$ of $\mathbf{x}$ is defined as [A1, A8]:

$$\mathcal{F}_g\{\mathbf{x}\} = \mathbf{V}^{-1}\mathbf{x}, \tag{2}$$

where $\mathbf{V}$ denotes the eigenvector matrix such that $\mathbf{M} = \mathbf{V}\mathbf{J}\mathbf{V}^{-1}$. The GFT indices are eigen values of adjacency matrix $\mathbf{M}$. To address generality of GFT, we mention that if $\mathbf{M}$ is a special circulant matrix then GFT coincides with the standard discrete Fourier transform (DFT). Attempts [A9, A10] were also made to **extend wavelet transforms**, **multi-resolution filters**, and **parametric dictionary learning** on graphs, mainly by using the concept of **graph Laplacian** from the **spectral graph theory**. Further, a **linear prediction** scheme on graph was also defined in [A1] where n'th shift is modeled by $\mathbf{M}^n\mathbf{x}$ as a **signal diffusion** mechanism; as shift increases, the effect of signal diffusion on the underlying graph increases. However, there is **no tangible effort to extend sparse processing to signals on graphs** – such as compressed sensing on graphs, sparse representation on graphs, low-rank matrix sensing on graphs, except very few attempts [A11]. To give an example, for dictionary learning on graphs, neither a non-parametric dictionary learning nor a generalization of DCT as a graph cosine transform **is done yet**.

Learning Over Networks

Learning over networks is a growing field today [A2] where the **main task is distributed estimation using distributed adaptation and optimization by exchanging information over networks**. Let $G = (\mathcal{V}, \mathcal{E})$ be a network graph for K nodes, and there exists a $K \times K$ **policy matrix** (also called **mixing matrix**) $\mathbf{S} = [s_{lk}]$ where s_{lk} is a policy weight between node pair (l, k). Typically the elements s_{lk} of $\mathbf{S}$ respect the graph topology, for example

$$s_{lk} = 0, \text{ if } (l,k) \notin \mathcal{E}. \tag{3}$$

For the l'th node, a signal of interest is estimated by a function of weighted average of estimates of all nodes where the weights are $\{s_{lk}\}_{k=1}^{K}$. Using policy matrix, there are several ways to cooperate by information exchange, for example, using **incremental strategy**, **consensus strategy** and **diffusion strategy**. To **minimize** the exchange of information over nodes such that estimation process converges, the policy matrix $\mathbf{S}$ should have certain analytical properties, such as stochastic, doubly stochastic, etc. In this paradigm, we may perform **analysis of average performance** such as mean square error.

Important Missing Aspects So Far

We have already mentioned that there is no tangible research effort in horizon to investigate sparse processing, signal processing on graphs and learning over networks in a holistic manner. The SparseNet project is aimed to mobilize such research effort, possibly **the first one in world**. As sparse processing is growing field with many proven results and practical schemes, SparseNet project will concentrate on few major sparse processing methods, but not limited to

1. compressed sensing (CS),
2. low-rank matrix sensing (LRMS),
3. dictionary learning,
4. sparse kernel machines,

for extending to graphs/networks. SparseNet will **consider** large-scale systems over graph/network where large-dimensional sparse processing tasks are executed in nodes. From the above survey of field, we enlist below the **important aspects that are missing** so far.

1. Distributed adaptive estimation of CS and LRMS on graphs/networks.
2. Dictionary learning on graphs/networks.
3. Investigating networks aspects, such as policy matrix, communication quality and protocol. For example, what happens if the network topology (graph) changes or there is link failure or if the network links are bandwidth constrained and need to use quantized data?
4. Average performance analysis.

Relevant Endeavor Including Our Works

1. Major works on distributed CS [A12] are realized for limited number of nodes, and **does not scale well for large setups as they do not consider network aspects**. For large number of nodes (more than 100 nodes), we have successfully designed distributed CS solutions where network has arbitrary connection topology with the aspect that policy weights s_{lk} are equal if $l \in \mathcal{N}_k$ where $\mathcal{N}_k$ denotes the set of neighboring nodes of the kth node. See [SC22, SC24, SC52, SC80]. The work of [SC80] is the first sound endeavor of its kind where a greedy algorithm for distributed CS is constructed and analyzed with provable performance guarantee using network parameters, RIP of sensors, and democratic voting based consensus principles. We believe that this new analysis results in a step jump towards designing computationally simple distributed greedy algorithms, even though with the **drawback** that the analysis belongs to the **worse case** approach. We have no work so far on distributed LRMS even though we worked on single sensor LRMS [SC12, SC64].
2. For distributed CS, we recently investigated imperfect links via coding [SC17, SC69, SC25].
3. To analyze algorithms for characterizing **average reconstruction performance**, we have used **replica method** for single sensor CS setup in [SC9, SC60, SC70, SC79].
4. We have recently started investigating signal processing over graphs and learning over networks. The relevant manuscripts are [SC78, SC81, SC82, SC83]. In [SC78] we started with the graph Fourier transform (GFT) of (2) and extended to define a new **Hilbert transform on graph** for the

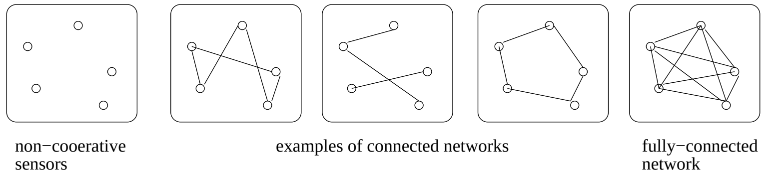

Figure 1: Examples of connected networks. The left panel is the disconnected one.

first time. Further, we considered **construction of a graph** in [SC81] such that a linear prediction on that graph performs usually better than a standard linear prediction, and also considered **signal denoising** and **inpainting** in [SC82]. Finally, in [SC83], we have considered learning over network for a consensus where the **policy matrix is sparse** to represent a communication resource constrained network.

A.4 Project Description

The **core** of this SparseNet project comprises of conceptualization and design of new sparse processing algorithms in **distributed** manners and performance analysis of those distributed algorithms considering **topology of graphs/networks**. Figure 1 shows several examples of networks. We would like to answer useful questions about such networked scenarios. **Relevant questions** are as follows.

- What aspects of network policy matrix influence performance?
- Which topology has best performance and how fast the best performance can be achieved by data exchange over network (that is called convergence rate)?
- Which topology does approach to the performance of a centralized or fully connected solution?
- Is cooperation always useful? What happens if too noisy data are exchanged or some network links are highly bandwidth constrained or in failure?
- What kind of graphs with ease of construction is natural for sparse processing, but still allows good algorithmic development and theoretical tractability?

To maximize the chance of success in SparseNet project, we plan to follow a **hedging strategy** in which we tackle related, yet not fully linked challenges, thus minimizing the risk to the project from the failure of a single component. In the following part, we describe four work packages and the research problems to be pursued. We also show how the project relates to our previous (published) and ongoing (submitted and unpublished) works. Finally we provide an **estimate of deliverables** in terms of publications. Along-with describing the targets of work packages and our technical approaches, we also briefly mention few **concrete research problems**.

WP1 ***Sparse Processing Over Networks***

The targets of WP1 are designing distributed algorithms that are optimized for network aspects, and analysis of the distributed algorithms. For achieving the targets, we will use network policy matrix $\mathbf{S}$ for cooperation. Using policy matrix, there are several ways to cooperate, such as incremental strategy, consensus strategy and diffusion strategy. For a degenerate policy matrix, we recently used democratic voting principles (majority voting) as a consensus strategy in distributed CS [SC24, SC52, SC80]. However majority voting provides a hard consensus and hence the theoretical analysis has a limited tractability. In SparseNet project, we will concentrate on **soft consensus** via convex combination of policy weighted information over networks. Let us concentrate on one example case for a distributed CS scenario. In relation to (1), suppose k'th node observes

$$\mathbf{y}^{(k)} = \mathbf{A}^{(k)}\ \mathbf{x}^{(k)} + \mathbf{w}^{(k)}, \tag{4}$$

and we consider the correlation model $\mathbf{x}^{(k)} = \mathbf{x} + \mathbf{x}_{\mathrm{p}}^{(k)}$, where $\mathbf{x}$ is a sparse signal common to every node (or sensor) and $\mathbf{x}_{\mathrm{p}}^{(k)}$ be the private sparse signal part ($\mathbf{x}_{\mathrm{p}}^{(k)}$ even can be an innovation signal). This simple correlation model is valid for a camera sensor network where several cameras are in surveillance to observe objects from different directions and angles. Note that, if private parts are null vectors, then the setup is meant for estimating a common signal $\mathbf{x}$. For a distributed CS setup using adaptive learning methods, first we define a policy update variable and a complimentary policy update variable as follows.

$$\begin{array}{ll} \text{policy update variable}: & \boldsymbol{\psi}^{(k)} = \sum_{l \in \mathcal{N}_k} s_{lk} \hat{\mathbf{x}}^{(k)}. \\ \text{complimentary policy update variable}: & \boldsymbol{\phi}^{(k)} = \sum_{l \in \mathcal{N}_k} s_{lk} \hat{\mathbf{x}}^{(k)} - s_{kk} \hat{\mathbf{x}}^{(k)} = \boldsymbol{\psi}^{(k)} - s_{kk} \hat{\mathbf{x}}^{(k)}. \end{array}$$

Note that the complimentary policy update variable $\boldsymbol{\phi}^{(k)}$ holds weighted information from neighboring connected sensors, but not the contribution from own. We now introduce a cost (or utility) function $C(\mathbf{x}^{(k)}, \{\mathbf{x}^{(l)}\}_{l \in \mathcal{N}_k}) : \mathbb{C}^N \times \mathbb{C}^N \times \ldots \times \mathbb{C}^N \rightarrow \mathbb{R}$ as follows:

$$C^{(k)} \triangleq C(\mathbf{x}^{(k)}, \{\mathbf{x}^{(l)}\}_{l \in \mathcal{N}_k}) = \lambda_1 \mathcal{E}\{\|\mathbf{y}^{(k)} - \mathbf{A}^{(k)} \mathbf{x}^{(k)}\|_2^2\} + \lambda_2 \|\mathbf{x}^{(k)}\|_1 + \lambda_3 \|\mathbf{x}^{(k)} - \boldsymbol{\phi}^{(k)}\|_1, \tag{5}$$

where $\lambda_1, \lambda_2, \lambda_3$ are user-defined positive weights satisfying $\lambda_1 + \lambda_2 + \lambda_3 = 1$. Note that the first part $\mathcal{E}\{\|\mathbf{y}^{(k)} - \mathbf{A}^{(k)} \mathbf{x}^{(k)}\|_2^2\}$ is the common mean square error utility cost used in many standard distributed multi-agent algorithms. The second part $\|\mathbf{x}^{(k)}\|_1$ promotes sparsity in solution. Finally the third part $\|\mathbf{x}^{(k)} - \boldsymbol{\phi}^{(k)}\|_1$ brings the effect of correlation. Now we concentrate on tools from adaptive gradient descent search algorithms (such as the famous LMS algorithm) via consensus and diffusion strategies [A13, A14]. Let i denotes time instant to exchange information over network. Then our strategy is

$$\begin{aligned} \forall k, \quad & \text{policy update}: \boldsymbol{\psi}_{i-1}^{(k)} = \sum_{l \in \mathcal{N}_k} s_{lk} \hat{\mathbf{x}}_{i-1}^{(k)}; \\ & \text{complimentary policy update}: \boldsymbol{\phi}_{i-1}^{(k)} = \boldsymbol{\psi}_{i-1}^{(k)} - s_{kk} \hat{\mathbf{x}}_{i-1}^{(k)} \\ & \text{gradient update}: \hat{\mathbf{x}}_i^{(k)} = \boldsymbol{\psi}_{i-1}^{(k)} - \mu_k \, \nabla_{\mathbf{x}^{(k)}} C_{i-1}^k, \end{aligned} \tag{6}$$

where μ_k is a step size, C_{i-1}^k is an instantaneous cost (due to practical issues that statistical moments are not available) as $C_{i-1}^k = \lambda_1 \|\mathbf{y}^{(k)} - \mathbf{A}^{(k)} \mathbf{x}_{i-1}^{(k)}\|_2^2 + \lambda_2 \|\mathbf{x}_{i-1}^{(k)}\|_1 + \lambda_3 \|\mathbf{x}_{i-1}^{(k)} - \boldsymbol{\phi}_{i-1}^{(k)}\|_1$, and

$$\nabla_{\mathbf{x}^{(k)}} C_{i-1}^k \triangleq \left[\frac{\partial C_{i-1}^k}{\partial x_1^{(k)}}, \, \frac{\partial C_{i-1}^k}{\partial x_2^{(k)}}, \, \ldots, \, \frac{\partial C_{i-1}^k}{\partial x_N^{(k)}} \right]^\top . \tag{7}$$

Note that the cost function has ℓ_1 norm penalty which is not differentiable and brings non-trivial sub-gradient issues which we believe can be addressed in our future endeavor. The task is to characterize $\forall k, \; \mathcal{E}\{\|\mathbf{x}^{(k)} - \hat{\mathbf{x}}^{(k)}\|_2^2\}$ as a function of signal correlations and the policy weights s_{lk}, in turn the policy matrix $\mathbf{S} = [s_{lk}]$. Then also to answer how fast the convergence happens, that means number of time instants to stabilize to the final estimates. Further, given a specified reconstruction quality, what **S** leads to lowest number of links? That means, we pursue for a sparse **S** to save communication resource; many zeros in **S** means no link connection. Naturally the approach will help us to investigate the question which topology does approach to the performance of a centralized or fully connected solution. We believe that our soft consensus based approach via gradient search will reveal **important clues on most of the questions** that we raised at the beginning of this section A.4.

We mention that gradient descent based adaptive learning is one way to achieve solutions over networks. **Alternatively**, we can use policy update variables in other ways – devising new approaches and reducing dependency on gradient search. For example we can use weighted ℓ_1 norm minimization where the weighting matrix can be defined via policy update variable as $W_{i-1}^{(k)} = [\mathrm{diag}[\boldsymbol{\psi}_{i-1}^{(k)}]]^{-1}$ and then solve for the following optimization problem

$$\hat{\mathbf{x}}_i^{(k)} = \arg\min_{\mathbf{x}^{(k)}} \|W_{i-1}^{(k)}\mathbf{x}^{(k)}\|_1 \text{ subject to } \|\mathbf{y}^{(k)} - \mathbf{A}^{(k)}\mathbf{x}^{(k)}\|_2 \leq \epsilon^{(k)}, \tag{8}$$

where $\epsilon^{(k)} \geq \mathbf{w}^{(k)}$ is user defined parameter to represent the allowable noise strength. Similarly gradient based and weighted nuclear norm minimization based solutions also can be envisaged for distributed LRMS where appropriate correlation model need to be used.

The engineering approaches discussed so far mainly for distributed CS problem are viable to extend for distributed low-rank matrix sensing and distributed dictionary learning problems. For example, in case of distributed LRMS, $\mathbf{x}^{(k)}$ is the vectorized form of a large low-rank matrix at the k'th node. Using appropriate models of correlations between low-rank matrices, the learning based estimation algorithms over networks follow similar concepts as discussed before. However, **a considerable challenge** will arise for designing sparse kernel machines over networks. The Sparse kernel machines – such as Bayesian relevance vector machine and sparse Bayesian learning algorithms – are maximum-a-posteriori (MAP) estimators. That means, the task is to estimate $p(\mathbf{x}|\mathbf{y})$ given likelihood function $p(\mathbf{y}|\mathbf{x})$ and sparsity promoting priors $p(\mathbf{x})$. The algorithms are **type II estimation** (machine learning) schemes where typically **evidence approximation** and **expectation-maximization** (EM) frameworks are used. We have worked for designing type II estimation algorithms in [SC75, SC76]. It is well known that EM is a **strong framework** in estimation and learning due to concept of hidden variables and information theoretic proof on monotonic convergence, with many applications in statistical signal processing and machine learning. However there is almost **no research work** to design **distributed evidence approximation** and **distributed EM algorithms**. A distributed EM example is [A15] where only specific distributed scenarios are addressed. Hence design of **distributed type II estimation** schemes is a totally **open research area** that will not only have a bearing on distributed sparse processing over networks in the scope of current project, but to the general machine learning area in a **foundational sense**.

WP2 ***Sparse Processing On Graphs***

The ℓ_2-norm based schemes are traditional and have profound implications in signal processing and machine learning. The ℓ_2-norm is **instrumental** in defining analytically tractable cost functions, such as mean square error (MSE), weighted mean square error (WMSE), etc. Using these cost functions and additional assumptions (either deterministic or probabilistic), some **classical** signal processing and machine learning schemes are least-squares, subspace estimation, Wiener filter, Kalman filter, linear prediction, auto-regression (AR), sparse kernel machines, eigen decomposition, Karhunen-Loeve transform (KLT) and many other transforms including DFT, DCT etc. To show an example, in the minimum mean square error sense, the best practical decorrelating transform of an AR-1 source is DCT at a large dimension, that means the optimal decorrelating transform (KLT) of AR-1 statistics converges to DCT in asymptotic sense. While KLT is a data dependent transform, the DCT is a fixed deterministic transform and hence used for image compression heavily. Further DFT, DCT and many other linear transforms are orthonormal and hence help to preserve isometry between original signal and transformed domains. This isometry preserving property – that means ℓ_2 distance between two points in original signal domain remains same in the transformed domain – is very useful is almost all signal processing and machine learning schemes. While some ℓ_2-norm based schemes, such as DFT and linear prediction, are attempted to extend on graphs, a plethora of existing schemes remains to have an extension and hence there exists immense **opportunity** to work in the new topic of signal processing on graphs. In WP2, we will consider an **impact-making** and **challenging** research problem – **development of statistical signal processing and Bayesian machine learning frameworks on graphs.** So far signal processing on graphs is restricted to deterministic domain, and a statistical framework on graphs does not exist.

Further, in signal processing and machine learning, the use of ℓ_1-norm in relevant cost functions to promote sparsity is already in practice. There exist **interesting connections** between ℓ_1 and ℓ_2 norms. To illustrate, for a Ndimensional real vector $\mathbf{x} = [x_1,\, x_2,\, \ldots, x_N]^\top$, the ℓ_1 norm is $\|\mathbf{x}\|_1 \triangleq \sum_{n=1}^{N} |x_n| = \sum_{n=1}^{N} \frac{x_n^2}{|x_n|} = \mathbf{x}^\top W(\mathbf{x})\,\mathbf{x}$, where $W(\mathbf{x})$ is a diagonal weighting matrix whose diagonal entries are $\frac{1}{|x_n|}$. It can be seen that ℓ_1 norm $\|\mathbf{x}\|_1$ can be represented by a weighted square ℓ_2-norm distance $\mathbf{x}^\top W(\mathbf{x})\,\mathbf{x}$. Using this **important connection** between ℓ_1 and ℓ_2 norms, several methods already have been developed for CS/LRMS reconstruction, for example iteratively reweighted least-squares (IRLS) algorithms [A16]. WP2 will use this **important connection to realize sparse processing on graphs**. Using the formal ℓ_2-norm based schemes, both existing and future ones, and then following appropriate weighting modifications to suit for sparsity promoting ℓ_1 norm, we will endeavor to extend many sparse processing schemes for generalization on graphs. **Our first attempt** using IRLS is [SC82] where we address signal denoising (estimation for noise reduction) and inpainting (missing data prediction). WP2 will consider **several interesting problems**, such as standard sparse processing methods on graphs, sparse linear prediction on graphs, sparse power spectrum estimation on graphs, sparse tracking on graphs, etc.

WP3 ***Fundamental Theoretical Analysis (A Concrete Research Problem Example)***
In the scope of WP3, we mention below a challenging theoretical research problem: **fundamental analysis for K-node setup**. By now we acknowledge that the analysis of a distributed CS setup is non-trivial, and naturally so for a distributed LRMS. In this direction, an important theoretical contribution (or major step) will be analyzing a K-node centralized setup that provides a benchmark performance (best performance to achieve) for a K-node distributed setup. This time we concentrate on a distributed LRMS instead of CS for more generality. Let $\mathbf{X}^{(k)}$ is a low-rank matrix and its vectorized form is $\mathbf{x}^{(k)} \triangleq \mathrm{vec}(\mathbf{X}^{(k)})$. In relation to (1), the observation model is $\mathbf{y}^{(k)} = \mathbf{A}^{(k)}\,\mathrm{vec}(\mathbf{X}^{(k)}) + \mathbf{w}^{(k)} = \mathbf{A}^{(k)}\,\mathbf{x}^{(k)} + \mathbf{w}^{(k)}$. Let us define a cross-correlation matrix $\mathbf{C}(\{\mathrm{vec}(\mathbf{X}^{(k)})\}) = \mathbf{C}(\{\mathbf{x}^{(k)}\}) = \mathbf{C} \triangleq \sum_{\forall k,l,k\neq l}(\mathbf{x}^{(k)})(\mathbf{x}^{(l)})^\top$. If $\mathbf{X}^{(k)}$ are highly inter-correlated, that means $\mathbf{x}^{(k)}$ are highly inter-correlated and the cross-correlation matrix $\mathbf{C}$ will be highly skewed or effectively low-rank. Using convex-relaxation of rank by nuclear norm of a matrix (analogous of using ℓ_1 norm to relax ℓ_0 norm in case of a sparse vector), we can formulate the following centralized optimization method

$$\min_{\mathbf{X}^{(k)}} \left\{ \sum_{\forall k} \|\mathbf{X}^{(k)}\|_\star + \lambda \|\mathbf{C}\|_\star \right\} \text{ subject to } \|\mathbf{y}^{(k)} - \mathbf{A}^{(k)}\,\mathrm{vec}(\mathbf{X}^{(k)})\|_2 \leq \epsilon^{(k)}, \tag{9}$$

where $\|.\|_\star$ denotes nuclear norm, λ represents the appropriate weight and the noise power $\|\mathbf{w}^{(k)}\|_2 \leq \epsilon^{(k)}$. The challenging tasks are design of practical algorithms and their theoretical analysis with respect to various parameters of the system, for example, rank of $\mathbf{X}^{(k)}$, rank of $\mathbf{C}$, properties of $\mathbf{A}^{(k)}$ and noise powers $\epsilon^{(k)}$. **This fundamental problem was never posed in the existing literature and we wish to use its theoretical analysis using replica methods and worst case analysis approaches.** Here we mention that this fundamental problem can be turned around to a **sensing resource allocation** problem. In that case, for a given number of total measurements, the question will be what is the set of optimal number of measurements in each sensor (or node), that means what are the dimensions of $\mathbf{y}^{(k)}$. We raised this sensing resource allocation problem in section A.2.

WP4 ***Validation of Algorithms for Real Data***
WP4 will consider validation experiments of algorithms developed in WP1, 2 and 3 on real signals/data, such as speech, audio and image signals in standard scopes of multimedia processing. For example, we are now constructing graphs for linear prediction of speech signal [SC81], and signal denoising and inpainting of speech and image signals [SC82]. Naturally we will test new sparse processing methods on graphs for speech, audio and image processing tasks. Further we will consider weather data of Europe

and across the world for many years and use the data for weather prediction problems. Then we will collect social networks' data and Internet blog data to analyze. Finally, we will consider to build a testbed camera network for the purpose of surveillance and benchmark our sparse processing algorithms over graphs/networks for the testbed.

Project Timeline: January 1, 2016 - December 31, 2019
Project Deliverables: Eight journal papers can be expected. Seven journal papers from WP1, Wp2 and WP3, and one journal paper from WP4.

A.5 Additional Information

A.5.1 Impact

The SparseNet project proposal comprises of several **novel** state-of-the-art research problems, including new **fundamental** theoretical problems with **foundational** aspects. The project bears a fascinating **interdisciplinary** flavor due to the use of methods from several fields, mainly from statistical physics and the engineering field of signals and systems. Besides high quality research contributions, an important outcome of the project will be the **graduation** of two Ph.D. scholars. The project will also have direct and indirect impacts on related and **collaborative** research issues, pursued by the members of Communication Theory, Signal Processing, Automatic Control and Biological Physics groups at KTH, Stockholm.

A.5.2 Preliminary Results

We have a focused and intensive activity in sparse processing, and published several articles in journals and conferences. Recently we started working in signal processing on graphs and learning over networks.

A.5.3 Project Organizations and Collaborations

The project will be lead by Dr. Saikat Chatterjee, Communication Theory (CT) Group, KTH. In addition, the project will directly involve two Ph.D. scholars, and indirectly involve seniors members from CT group, Signal Processing, Automatic Control and Biological Physics groups of KTH. In relation to the proposal, **the applicant's main national and international collaborators** are shown in Table 1.

Table 1: Collaboration by the applicant Saikat Chatterjee (citations are from the publication list)

US and Asia	
Oregon State University, Oregon, US	[SC18]
Indian Institute of Science, Bangalore, India	[SC16, SC23, SC1, SC2, SC6]
Tsinghua University, Beijing, China	[SC18]
Beijing University of Posts and Telecommunications, China	[SC19]
Tokyo Institute of Technology, Japan	[SC9, SC60, SC49]
Europe, Australia and Oceania	
NTNU Norwegian University of Science and Technology, Norway	[SC62, SC10, SC15, SC42, SC62]
Aalto University, Helsinki, Finland	[SC18, SC79]
University of Helsinki, Helsinki, Finland	[SC18]
University of Luxembourg, Luxembourg	[SC54]
KTH Royal Institute of Technology, Stockholm, Sweden	[SC11, SC12, SC13] and ...
Victoria University of Wellington, New Zealand	[SC19]

A.5.4 Towards the VR Initiative for Collaboration with India

We mention about the Swedish Research Council (VR) notification on collaboration with India ("Avsiktsörklaring med Indien"). VR and DST India have jointly floated regular project submission call. Right now we have an ongoing collaboration with Prof. K.V.S. Hari from Indian Institute of Science, Bangalore, India to develop a novel fusion framework for CS [SC16, SC23]. Therefore, we hope to strengthen this existing collaboration. Also we will look for new collaboration with prestigious Indian Institute of Technologies (IITs) in future scope of VR/SSF/VINNOVA notifications.

A.5.5 Other Grants

This SparseNet proposal is not included in any other application or project.

References

[A1] A. Sandryhaila and J. M. F. Moura, "Discrete signal processing on graphs," *IEEE Trans. Signal Process.*, vol. 61, no. 7, pp. 1644–1656, 2013.
[A2] A. Sayed, *Adaptation, Learning, and Optimization over Network*. Foundations and Trends in Machine Learning, NOW Publishers, 2014.
[A3] M. Elad, *Sparse and redundant representations: From theory to applications in signal and image processing*. Springer, 2010.
[A4] R. Baraniuk, M. Davenport, R. Devore, and M. Wakin, "A simple proof of the restricted isometry property for random matrices," *Constr. Approx*, vol. 2008, 2007.
[A5] V. Dotsenko, *Introduction to the replica theory of disordered statistical systems*. New York: Cambridge University Press, 2001.
[A6] S. Rangan, A. Fletcher, and V. Goyal, "Asymptotic analysis of map estimation via the replica method and applications to compressed sensing," *Information Theory, IEEE Transactions on*, vol. 58, no. 3, pp. 1902 –1923, march 2012.
[A7] D. I. Shuman, S. Narang, P. Frossard, A. Ortega, and P. Vandergheynst, "The emerging field of signal processing on graphs: Extending high-dimensional data analysis to networks and other irregular domains," *IEEE Signal Process. Mag.*, vol. 30, no. 3, pp. 83–98, 2013.
[A8] A. Sandryhaila and J. M. F. Moura, "Big data analysis with signal processing on graphs: Representation and processing of massive data sets with irregular structure," *IEEE Signal Process. Mag.*, vol. 31, no. 5, pp. 80–90, 2014.
[A9] D. K. Hammond, P. Vandergheynst, and R. Gribonval, "Wavelets on graphs via spectral graph theory," *Appl. Computat. Harmonic Anal.*, vol. 30, no. 2, pp. 129–150, 2011.
[A10] D. Thanou, D. I Shuman, and P. Frossard, "Learning parametric dictionaries for signals on graphs," *IEEE Trans. Signal Process.*, vol. 62, no. 15, pp. 3849–3862, 2014.
[A11] M. Zheng, J. Bu, C. Chen, C. Wang, L. Zhang, G. Qiu, and D. Cai, "Graph regularized sparse coding for image representation," *IEEE Transactions on Image Processing*, vol. 20, no. 5, pp. 1327–1336, 2011.
[A12] D. Baron, M. Duarte, M. Wakin, S. Sarvotham, and R. Baraniuk, "Distributed compressive sensing," *http://arxiv.org/abs/0901.3403*, jan. 2009.
[A13] J. Chen and A. Sayed, "Diffusion adaptation strategies for distributed optimization and learning over networks," *Signal Processing, IEEE Transactions on*, vol. 60, no. 8, pp. 4289–4305, Aug 2012.
[A14] A. Sayed, S.-Y. Tu, J. Chen, X. Zhao, and Z. Towfic, "Diffusion strategies for adaptation and learning over networks: an examination of distributed strategies and network behavior," *Signal Processing Magazine, IEEE*, vol. 30, no. 3, pp. 155–171, May 2013.
[A15] D. K. Jason Wolfe, Aria Haghighi, "Fully distributed em for very large datasets," in *International conference on machine learning (ICML)*, 2008.
[A16] I. Daubechies, R. DeVore, M. Fornasier, and C. S. Gunturk, "Iteratively reweighted least squares minimization for sparse recovery," *Communications on Pure and Applied Mathematics*, vol. 63, no. 1, pp. 1–38, 2010. [Online]. Available: http://dx.doi.org/10.1002/cpa.20303

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	Saikat Chatterjee	33

Salaries including social fees

	Role in the project	Name	Percent of salary	2016	2017	2018	2019	Total
1	Applicant	Saikat Chatterjee	33	293,000	301,000	310,000	320,000	1,224,000
2	Participating researcher	Existing PhD student	50	245,000	260,000	295,000	328,000	1,128,000
3	Participating researcher	New PhD student	50	245,000	260,000	295,000	328,000	1,128,000
	Total			783,000	821,000	900,000	976,000	3,480,000

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 space	80,000	90,000	100,000	100,000	370,000
	Total	80,000	90,000	100,000	100,000	370,000

Running Costs

Running Cost	Description	2016	2017	2018	2019

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	783,000	821,000	900,000	976,000	3,480,000	1,353,000	4,833,000
Running costs					0		0
Depreciation costs					0		0
Premises	80,000	90,000	100,000	100,000	370,000		370,000
Subtotal	863,000	911,000	1,000,000	1,076,000	3,850,000	1,353,000	5,203,000
Indirect costs	315,858	327,960	366,000	387,360	1,397,178	495,410	1,892,588
Total project cost	1,178,858	1,238,960	1,366,000	1,463,360	5,247,178	1,848,410	7,095,588

Explanation of the proposed budget

Briefly justify each proposed cost in the stated budget.

Explanation of the proposed budget*

As described by the project budget and time frame, we plan to engage two PhD students and the applicant Saikat Chatterjee. The project fund will be used to partly support Dr. Saikat Chatterjee, and two Ph.D. scholars. Dr. Saikat Chatterjee will be funded at 33% and the two Ph.D. scholars will be funded at 50%. Both PhD students will however be active at 80% in the project. We plan that a current Ph.D. scholar will continue his research direction of designing systems and algorithms. We will recruit a new Ph.D. scholar for pursuing theoretical studies. The salaries of Dr. Saikat Chatterjee and two Ph.D. scholars are computed based on the estimate of 45 kSEK/month and 27 kSEK/month with 3% annual upward revision. The remaining 30% part of the time of PhD students will be funded by teaching fund and KTH funds; the corresponding cost is shown as 'other costs'.

To get the figures for indirect costs, the following data were used (as supplied by the head of economics for KTH School of Electrical Engineering, for the year 2015 and also projected to be used for the years 2016-19).

KTH central administration OH: 23.6%
KTH School of Electrical Engg OH: 6.3%
Dept of Communication Theory, KTH EES OH: 6.7%

The OH values are used to the direct cost of the salaries.

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

Curriculum Vitae

Saikat Chatterjee

Academic degrees

1. Ph.D. in Electrical Communication Engineering
   Institution: Indian Institute of Science, Bangalore, India
   Degree awarded on March 25, 2009
   Specialization: Signal Processing
   Thesis title: "Rate-distortion performance and complexity optimized strutured vector quantization"
   Doctoral supervisor: Prof. T.V. Sreenivas, Dept of ECE, Indian Institute of Science.
2. M.E. in Electronics and Telecommunication Engineering
   Institution: Jadavpur University, India
   Degree awarded in 2002
   Specialization: Control Engineering
   Thesis topic: Real time fuzzy logic based intelligent control system design
   Award: *Secured 1st rank in the class (recipient of university medal)*
3. B.E. in Electrical Engineering
   Institution: Jadavpur University, India
   Degree awarded in 1999
   Specialization: Power Systems

Present position

Permanent researcher (from 2012-11-01), Communication Theory Lab, KTH

Previous employments

2009-12 Post-doc researcher, Communication Theory Lab, KTH
2008-09 Post-doc researcher, Sound and Image Processing Lab, KTH
2008 Research associate, Indian Institute of Science, India
2003-08 Doctoral student, Indian Institute of Science, India
2002-03 Lecturer in Asansol Engineering College, India

Information about appointment as a docent

Currently my formal docent application is under review by KTH central authority. I have to appear for the docent interview on 29th April 2015.

Supervision of doctoral students

I have co-supervised or currently co-supervising following students. The documented proof of supervision is furnished via citation of research publications shown in the publication list. Typically in my co-supervision role, I am responsible as the main scientific advisor.

May 2013 Dr. Dave Zachariah, KTH
Thesis title: "Estimation for sensor fusion and sparse signal processing"
My role: Co-supervisor (as main scientific advisor)
Documented proof: Research publications are [SC12, SC13, SC53, SC14, SC64].
Main supervisor: Prof. Magnus Jansson

April 2014 Dr. Amirpasha Shirazinia, KTH
Thesis title: “Source and channel coding for compressed sensing and control”
My role: Co-supervisor (as main scientific advisor)
Documented proof: Research publications are [SC59, SC17, SC69, SC25].
Main supervisor: Prof. Mikael Skoglund

May 2014 Dr. Dennis Sundman, KTH
Thesis title: “Greedy algorithms for distributed compressed sensing”
My role: Co-supervisor (as main scientific advisor)
Documented proof: Research publications are [SC52, SC63, SC67, SC22, SC24, SC80].
Main supervisor: Prof. Mikael Skoglund

2012 – Mr. Martin Sundin, KTH
Project topic: Machine learning for sparse processing
My role: Co-supervisor (as main scientific advisor)
Documented proof: Research publications are [SC66, SC75, SC76].
Main supervisor: Prof. Magnus Jansson

2014 – Mr. Arun Venkitaraman, KTH
Project topic: Graph signal processing
My role: Co-supervisor (as main scientific advisor)
Documented proof: Research publications are [SC81].
Main supervisor: Prof. Peter Händel

Achievements and Fellowships

2010 – **Leading research activity in KTH on the thriving field - “compressive sensing and sparse signal processing”**. On this research field, co-supervisor of several PhD students in the role of main scientific advisor.

2014 **Invited for giving tutorial on “Sparse systems” in Swe-CTW 2014**

2014 Invited paper in SPCOM 2014 on “machine learning for sparse processing”.

2014 Invited paper in Journal of Sensor and Actuator Networks on “distributed compressed sensing”

2013 Invited paper in IEEE CAMSAP 2013 on “statistical signal processing”

2013 Invited paper in IEEE GlobalSIP 2013 on “distributed compressed sensing”

2013 **Invited paper in Eusipco 2013 for a special session titled “Trends in Sparse Signal Processing: Theory and Algorithm Design”**

2010 **Co-author of the best student paper award at ICASSP 2010 on the topic “Automatic speech recognition”**

2003-08 Institute fellowship by Indian Institute of Science (for pursuing Ph.D.)

2002 **Secured 1st rank in Masters of Engineering (recipient of university medal)**

2000-02 University Grant Commission India scholarship for pursuing Masters degree on the basis of pan Indian GATE (Graduate Aptitude Test in Engineering) score

2000 Scored among top 4% in pan Indian GATE examination

1995 Ranked 394th in state level JEE - Joint Entrance Examination - for pursuing Bachelor of Engineering (among 60,000 candidates)

Publication list

Publication List of Saikat Chatterjee

Summary statistics of publications from 2007

Published journal papers	25
Published conference papers	53
Total published papers	78
Manuscripts submitted or under preparation - related to SparseNet project	5

Citation statistics

Source: Google Scholar (click here), March 30, 2015.

	All	Since 2010
Citations	482	449
h-index	12	11
i10-index	13	12

Top-five most relevant papers for the application: [SC9, SC22, SC25, SC52, SC78].

List shown in year and subject wise

1. Peer-reviewed original articles (journals)

2007

Speech processing (speech coding)

[SC1] **S. Chatterjee** and T.V. Sreenivas, “Conditional PDF-based split vector quantizatization of wideband LSF parameters”, *IEEE Signal Processing Letters*, vol. 14, No. 9, pp. 641- 644, September 2007.

[SC2] **S. Chatterjee** and T.V. Sreenivas, “Analysis of conditional PDF based split VQ”, *IEEE Signal Processing Letters*, vol. 14, No. 11, pp. 781-784, November 2007.

2008

Speech processing (speech coding)

[SC3] **S. Chatterjee** and T.V. Sreenivas, “Switched conditional PDF-based split VQ using Gaussian mixture model”, *IEEE Signal Processing Letters*, vol. 15, pp. 91-94, 2008.

[SC4] **S. Chatterjee** and T.V. Sreenivas, “Predicting VQ performance bound for LSF coding”, *IEEE Signal Processing Letters*, vol. 15, pp. 166-169, 2008.

[SC5] **S. Chatterjee** and T.V. Sreenivas, “Optimum transform domain split VQ”, *IEEE Signal Processing Letters*, vol. 15, pp. 285-288, 2008.

[SC6] **S. Chatterjee** and T.V. Sreenivas, “Optimum switched split vector quantization of LSF parameters”, *Signal Processing*, vol. 88, Issue 6, pp. 1528-1538, June 2008.

2009

Speech processing (speech coding)

[SC7] **S. Chatterjee** and T.V. Sreenivas, “Reduced complexity two stage vector quantization”, *Digital Signal Processing*, vol. 19, pp. 476-490, May 2009.

2011

Speech processing (automatic speech recognition)

[SC8] **S. Chatterjee** and W.B. Kleijn, "Auditory model based design and optimization of feature vectors for automatic speech recognition", *IEEE Trans. Audio, Speech, Language Processing*, vol. 19, Issue 6, pp. 1813-1825, August 2011.

2012

Statistical physics and information theory based analysis

[SC9] Y. Kabashima, M. Vehkaperä and **S. Chatterjee**, "Typical l_1-recovery limit of sparse vectors represented by concatenation of random orthogonal matrices", *Journal of Statistical Mechanics: Theory and Experiments*, P12003, 2012.

Machine learning and statistical signal processing

[SC10] J.T. Flåm, **S. Chatterjee**, K. Kansanen and T. Ekman, "On MMSE estimation - A linear model under Gaussian mixture statistics", *IEEE Trans. Signal Processing*, vol. 60, Issue 7, pp. 3840-3845, 2012.

Sparse systems (compressed sensing and low-rank-matrix reconstruction)

[SC11] **S. Chatterjee**, D. Sundman, M. Vehkaperä and M. Skoglund, "Projection-based and look ahead strategies for atom selection", *IEEE Trans. Signal Processing*, Vol. 60, Issue 2, pp. 634-647, 2012.

[SC12] D. Zachariah, M. Sundin, M. Jansson and **S. Chatterjee**, "Alternating least-squares for low-rank matrix reconstruction", *IEEE Signal Processing Letters*, vol. 19, Issue 4, pp. 231-234, 2012.

[SC13] D. Zachariah, **S. Chatterjee** and M. Jansson, "Dynamic iterative pursuit", *IEEE Trans. Signal Processing*, vol. 60, Issue 9, pp. 4967-4972, 2012.

2013

Machine learning and statistical signal processing

[SC14] D. Zachariah, P. Wirfält, M. Jansson and **S. Chatterjee**, "Line spectrum estimation with probabilistic priors", *Signal Processing*, vol. 93, Issue 11, pp. 2969-2974, 2013.

[SC15] J.T. Flåm, D. Zachariah, Mikko Vehkaperä and **S. Chatterjee**, "The linear model under mixed Gaussian inputs: Designing the transfer matrix", *IEEE Trans. Signal Processing*, vol. 61, Issue 21, pp. 5247-5259, 2013.

Sparse systems (compressed sensing and low-rank-matrix reconstruction)

[SC16] S.K. Ambat, **S. Chatterjee**, and K.V.S Hari, "Fusion of algorithms for compressed sensing", *IEEE Trans. Signal Processing*, vol. 61, Issue 14, pp. 3699-3704, 2013.

[SC17] A. Shirazinia, **S. Chatterjee** and M. Skoglund, "Analysis-by-synthesis quantization for compressed sensing measurements", *IEEE Trans. Signal Processing*, vol. 61, Issue 2, pp. 5789-5800, 2013.

2014

Bioinformatics

[SC18] **S. Chatterjee**, D. Koslicki, S. Dong, N. Innocenti, L. Cheng, Y. Lan, M. Vehkaperä, M. Skoglund, L.K. Rasmussen, E. Aurell and J. Corander, "SEK: Sparsity exploiting k-mer-based estimation of bacterial community composition", *Bioinformatics*, 2014.

Speech processing (speech coding)

[SC19] Z. Ma, **S. Chatterjee**, W.B. Kleijn and J. Guo, "Dirichlet mixture modeling to estimate an empirical lower bound for LSF quantization", *Signal Processing*, vol. 104, pp. 291-295, 2014.

Machine learning and statistical signal processing

[SC20] D. Zachariah, N. Shariati, M. Bengtsson, M. Jansson and **S. Chatterjee** "Estimation for the linear model with uncertain covariance matrices", *IEEE Trans. Signal Processing*, vol. 62, Issue 6, pp. 1525-1535, 2014.

Sparse systems (compressed sensing and low-rank-matrix reconstruction)

[SC21] S.K. Ambat, **S. Chatterjee**, and K.V.S Hari, "Progressive fusion of reconstruction algorithms for low latency applications in compressed sensing", *Signal Processing*, vol. 97, Issue 4, pp. 146-151, 2014.

[SC22] D. Sundman, **S. Chatterjee**, and M. Skoglund, "Methods for distributed compressed sensing", *Journal of Sensor and Actuator Networks*, Issue 3(1), pp. 1-25, 2014 **(Invited paper)**.

[SC23] S.K. Ambat, **S. Chatterjee**, and K.V.S Hari, "A committee machine approach for compressed sensing reconstruction", *IEEE Trans. Signal Processing*, vol. 62, Issue 7, pp. 1705-1717, 2014.

[SC24] D. Sundman, **S. Chatterjee** and M. Skoglund, "Distributed greedy pursuit algorithms", *Signal Processing*, vol. 105, Issue 0, pp. 298-315, 2014.

[SC25] A. Shirazinia, **S. Chatterjee** and M. Skoglund, "Joint source-channel vector quantization for compressed sensing", *IEEE Trans. Signal Processing*, vol. 62, Issue 14, pp. 3667-3681, 2014.

2. Peer-reviewed conference contributions

2007

Speech processing (speech coding)

[SC26] **S. Chatterjee** and T.V. Sreenivas, "Computationally efficient optimum weighting function for vector quantization of LSF parameters", in ISSPA 2007, Sharjah, UAE.

[SC27] **S. Chatterjee** and T.V. Sreenivas, "Joint inter-frame and intra-frame predictive coding of LSF parameters", in ISSPA 2007, Sharjah, UAE.

[SC28] **S. Chatterjee** and T.V. Sreenivas, "Sequential split vector quantization of LSF parameters using conditional PDF", in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2007, USA.

[SC29] **S. Chatterjee** and T.V. Sreenivas, "Normalized two stage SVQ for minimum complexity wide-band LSF quantization", in Conference of the International Speech Communication Association (INTERSPEECH) 2007, Antwerp, Belgium.

[SC30] **S. Chatterjee** and T.V. Sreenivas, "Gaussian mixture model based switched split vector quantization of LSF parameters", in IEEE Symposium on Signal Processing and Information Technology (ISSPIT) 2007, Egypt.

2008

Speech processing (speech enhancement)

[SC31] A. Kundu, **S. Chatterjee** and T.V. Sreenivas, "Subspace based speech enhancement using Gaussian mixture model", in Conference of the International Speech Communication Association (INTERSPEECH) 2008, Brisbane, Australia.

[SC32] A. Kundu, **S. Chatterjee** and T.V. Sreenivas, "Speech enhancement using intra-frame dependency in DCT domain", in European Signal Processing Conference (EUSIPCO) 2008, Lausanne, Switzerland.

[SC33] A. Kundu, **S. Chatterjee**, A.S. Murthy and T.V. Sreenivas, "GMM based Bayesian approach to speech enhancement in signal/transform domain", in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2008, Las Vegas, USA.

Speech processing (speech coding)

[SC34] **S. Chatterjee** and T.V. Sreenivas, “Low complexity wide-band LSF quantization using GMM of uncorrelated Gaussian Mixtures”, in European Signal Processing Conference (EUSIPCO) 2008, Lausanne, Switzerland.

2009

Speech processing (automatic speech recognition)

[SC35] **S. Chatterjee**, C. Koniaris and W.B. Kleijn, “Auditory model based optimization of MFCCs improves automatic speech recognition performance”, in Conference of the International Speech Communication Association (INTERSPEECH) 2009, Brighton, U.K.

Speech processing (speech coding)

[SC36] **S. Chatterjee** and T.V. Sreenivas, “Analysis-by-systhesis based switched transform domain split VQ using Gaussian mixture model”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2009, Taiwan.

2010

Speech processing (automatic speech recognition)

[SC37] C. Koniaris, **S. Chatterjee** and W.B. Kleijn, “Selecting static and dynamic features using an adavnced audioty model for speech recognition”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2010, Dallas, USA. **(Best student paper award at ICASSP 2010).**

[SC38] **S. Chatterjee** and W.B. Kleijn, “Audioty model based modified MFCC features”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2010, Dallas, USA.

Speech processing (speech coding)

[SC39] **S. Chatterjee** and M. Skoglund, “Structured Gaussian Mixture model based product VQ”, in European Signal Processing Conference (EUSIPCO) 2010, Denmark.

Sparse systems (compressed sensing and low-rank-matrix reconstruction)

[SC40] D. Sundman, **S. Chatterjee** and M. Skoglund, “On the use of compressive sampling for wide-band spectrum sensing”, in IEEE Symposium on Signal Processing and Information Technology (ISSPIT) 2010, Luxor, Egypt.

[SC41] **S. Chatterjee**, D. Sundman and M. Skoglund, “Statistical post-processing improves basis pursuit denoising performance”, in IEEE Symposium on Signal Processing and Information Technology (ISSPIT) 2010, Luxor, Egypt.

2011

Machine learning and statistical signal processing

[SC42] J.T. Flåm, J. Jalden and **S. Chatterjee**, “Gaussian mixture modeling for source localization”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2011, Prague.

Statistical physics and information theory based analysis

[SC43] M. Vehkaperä, **S. Chatterjee** and M. Skoglund, “Analysis of MMSE estimation for compressive sensing of block sparse signals”, in Information Theory Workshop (ITW) 2011, Brazil.

Sparse systems (compressed sensing and low-rank-matrix reconstruction)

[SC44] **S. Chatterjee**, D. Sundman and M. Skoglund, "Robust matching pursuit for recovery of Gaussian sparse signal", in DSP/SPE Workshop 2011, Sedona, USA.

[SC45] **S. Chatterjee**, D. Sundman and M. Skoglund, "Look ahead orthogonal matching pursuit", in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2011, Prague.

[SC46] D. Sundman, **S. Chatterjee** and M. Skoglund, "Greedy pursuits of compressed sensing of jointly sparse signals", in European Signal Processing Conference (EUSIPCO) 2011, Barcelona.

[SC47] **S. Chatterjee**, D. Sundman, M. Vehkaperä and M. Skoglund, "Hybrid greedy pursuit", in European Signal Processing Conference (EUSIPCO) 2011, Barcelona.

[SC48] D. Sundman, **S. Chatterjee** and M. Skoglund, "Look ahead parallel pursuit", in IEEE Swedish Communication Technologies Workshop (Swe-CTW), 2011, Stockholm, Sweden.

2012

Statistical physics and information theory based analysis

[SC49] M. Vehkaperä, Y. Kabashima, **S. Chatterjee**, E. Aurell, M. Skoglund and L.K. Rasmussen, "Analysis of sparse representations using Bi-orthogonal dictionaries", in Information Theory Workshop (ITW) 2012, Switzerland.

Sparse systems (compressed sensing and low-rank-matrix reconstruction)

[SC50] S.K. Ambat, **S. Chatterjee** and K.V.S Hari, "Adaptive selection of search space in look ahead orthogonal matching pursuit", in National Communication Conference (NCC) 2012, India.

[SC51] **S. Chatterjee**, K.V.S Hari, P. Händel and M. Skoglund, "Projection-based atom selection in orthogonal matching pursuit for compressive sensing", in National Communication Conference (NCC) 2012, India.

[SC52] D. Sundman, **S. Chatterjee** and M. Skoglund, "A greedy pursuit algorithm for distributed compressed sensing", in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2012, Kyoto, Japan.

[SC53] D. Zachariah, **S. Chatterjee** and M. Jansson, "Dynamic subspace pursuit", in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2012, Kyoto, Japan.

[SC54] M.R. Bhavani Shankar, **S. Chatterjee** and B. Ottersten, "Detection of sparse random signals using compressive measurements", in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2012, Kyoto, Japan.

[SC55] S.K. Ambat, **S. Chatterjee**, and K.V.S Hari, "Fusion of greedy pursuits for compressed sensing signal reconstruction", in European Signal Processing Conference (EUSIPCO) 2012, Romania.

[SC56] S.K. Ambat, **S. Chatterjee**, and K.V.S Hari, "Subspace pursuit embedded in orthogonal matching pursuit", in TENCON 2012, Phillipines.

[SC57] S.K. Ambat, **S. Chatterjee**, and K.V.S Hari, "On selection of search space dimension in compressive sampling matching pursuit", in TENCON 2012, Phillipines.

[SC58] D. Sundman, **S. Chatterjee** and M. Skoglund, "FROGS: A serial reversible greedy search algorithm", in IEEE Swedish Communication Technologies Workshop (Swe-CTW), 2012, Stockholm, Sweden.

[SC59] A. Shirazinia, **S. Chatterjee** and M. Skoglund, "Performance bounds for vector quantized compressive sensing", in International Symp. on Info. Theory and its Applications (ISITA) 2012, Hawaii, USA.

2013

Statistical physics and information theory based analysis

[SC60] M. Vehkaperä, Y. Kabashima and **S. Chatterjee**, "Statistical mechanics approach to sparse noise denoising", in EUSIPCO 2013, Morocco **(Invited paper)**.

Machine learning and statistical signal processing

[SC61] D. Zachariah, M. Jansson and **S. Chatterjee**, "Enhanced Capon beamformer using regularized covariance matching", in IEEE Workshop on Computational Advances in Multi-Sensor Adaptive Proc. (CAMSAP) 2013, Saint Martin **(Invited paper)**.

[SC62] J.T. Flåm, E. Bjornson and **S. Chatterjee**, “Pilot design for MIMO channel estimation: an alternative approach to the Kronecker structure assumption”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2013, Canada.

Sparse systems (compressed sensing and low-rank-matrix reconstruction)

[SC63] D. Sundman, D. Zachariah, **S. Chatterjee** and M. Skoglund, “Distributed predictive subspace pursuit”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2013, Canada.

[SC64] D. Zachariah, **S. Chatterjee** and M. Jansson, “Iteratively reweighted least squares for reconstruction of low-rank matrices with linear structure”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2013, Canada.

[SC65] S.K. Ambat, **S. Chatterjee**, and K.V.S Hari, “Fusion of algorithms for compressed sensing”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2013, Canada.

[SC66] M. Sundin, M. Jansson and **S. Chatterjee**, “Conditional LMMSE for sparse signal estimation”, in EUSIPCO 2013, Morocco.

[SC67] D. Sundman, **S. Chatterjee** and M. Skoglund, “Parallel pursuit for distributed compressed sensing”, in IEEE GlobalSIP 2013 **(Invited paper)**.

[SC68] A. Shirazinia, **S. Chatterjee** and M. Skoglund, “Analysis-by-synthesis-based quantization of compressed sensing measurements”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2013, Canada.

[SC69] A. Shirazinia, **S. Chatterjee** and M. Skoglund, “Channel-optimized vector quantizer for compressed sensing measurements”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2013, Canada.

2014

Statistical physics and information theory based analysis

[SC70] M. Vehkaperä, Y. Kabashima and **S. Chatterjee**, “Analysis of regularized LS reconstruction and random matrix ensembles in compressed sensing”, in IEEE International Symposium on Information Theory (ISIT), 2014, Hawaii, USA.

Speech processing (automatic speech recognition)

[SC71] C. Koniaris and **S. Chatterjee**, “A sparsity based preprocessing for noise robust speech recognition”, in IEEE Spoken Langulage Technology workshop (SLT) 2014, USA.

Sparse systems (compressed sensing and low-rank-matrix reconstruction)

[SC72] P.B. Swamy, S.K. Ambat, **S. Chatterjee** and K.V.S Hari, “Reduced look ahead orthogonal matching pursuit”, in National Communication Conference (NCC) 2014, India.

[SC73] K. Li, C. Rojas, **S. Chatterjee** and H. Hjalmarsson, “Piecewise Toeplitz matrices-based sensing for rank minimization”, in European Signal Processing Conference (EUSIPCO), 2014, Portugal.

[SC74] A. Shirazinia, **S. Chatterjee** and M. Skoglund, “Distributed quantization for compressed sensing”, in IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2014, Italy.

Machine learning and statistical signal processing

[SC75] M. Sundin, **S. Chatterjee** and M. Jansson, “Combined modeling of sparse and dense noise improves Bayesian RVM”, in European Signal Processing Conference (EUSIPCO), 2014, Portugal.

[SC76] M. Sundin, **S. Chatterjee** and M. Jansson, “Relevance singular vector machine for low-rank matrix sensing”, in International Conference on Signal Processing and Communication (SPCOM) 2014, Bangalore, India **(Invited paper)**.

2015

Machine learning and statistical signal processing

[SC77] M. Sundin, **S. Chatterjee** and M. Jansson, “Greedy minimization of ℓ_1-norm with high empirical success”, accepted for IEEE conf. Acoustics, Speech and Signal Proc. (ICASSP) 2015, Australia.

Signal processing on graphs

[SC78] A. Venkitaraman, **S. Chatterjee** and P. Händel, “On Hilbert transform of signals on graphs”, accepted for Sampling Theory and Applications (SampTA), 2015, USA.

3. Manuscripts submitted or under preparation - related to SparseNet project

[SC79] M. Vehkaperä, Y. Kabashima and **S. Chatterjee**, “Analysis of regularized LS reconstruction and random matrix ensembles in compressed sensing”, *submitted to IEEE Trans. Information Theory*, website:http://arxiv.org/abs/1312.0256.

[SC80] D. Sundman, **S. Chatterjee** and M. Skoglund, “Design and analysis of a greedy pursuit for distributed compressed sensing”, *submitted to IEEE Trans. Signal Processing*, website:http://arxiv.org/abs/1403.6974.

[SC81] A. Venkitaraman, **S. Chatterjee** and P. Händel, “Graph linear prediction results in smaller error than standard linear prediction”, *submitted to EUSIPCO 2015*.

[SC82] A. Venkitaraman, M. Sundin, **S. Chatterjee** and P. Händel, “IRLS denosing and inpainting of signals on graphs”, *Under preparation*.

[SC83] M. Sundin, A. Venkitaraman, **S. Chatterjee** and M. Jansson, “Design of sparse mixing matrix for connected network”, *Under preparation*.

4. Open access computer programs

Motivated by the philosophy of reproducible research, I provide codes online with open access. The codes can be freely downloaded and then verified against the experimental plots shown in my publications. Please see: http://www.kth.se/ees/omskolan/organisation/avdelningar/commth/research/software.

CV

Name: Saikat Chatterjee	**Doctorial degree:** 2009-03-25
Birthdate: 19770314	**Academic title:** Doktor
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Research education

Dissertation title (swe)

Dissertation title (en)

Rate-distortion performance and complexity optimized strutured vector quantization

Organisation	Unit	Supervisor
Indian Institute of Science, Bangalore, India, India Not Sweden - Higher Education institutes	Department of Electrical Communication Engineering	Thippur Venkat Sreenivas

Subject doctors degree	ISSN/ISBN-number	Date doctoral exam
20205. Signalbehandling		2009-03-25

Publications

Name: Saikat Chatterjee	**Doctorial degree:** 2009-03-25
Birthdate: 19770314	**Academic title:** Doktor
Gender: Male	**Employer:** Kungliga Tekniska högskolan

Chatterjee, Saikat 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.