



Wednesday July 9, 8.30-12.10 am

Wegener	8.30-9.30 <i>Approximation by crystal invariant subspaces</i> Ursula Molter Chair: Alexandre d'Aspremont
Phase Retrieval (invited session) Chair: Tom Goldstein & Irène Waldspurger	
A9 Amphi 1	10.05-10.30 <i>3D Phaseless Imaging at Nano-scale: Challenges and Possible Solutions</i> Mahdi Soltanolkotabi
A9 Amphi 1	10.30-10.55 <i>Optimally Sample-Efficient Phase Retrieval with Deep Generative Models</i> Oscar Leong, Paul Hand & Vladislav Voroninski
A9 Amphi 1	10.55-11.20 <i>The Cramer-Rao Lower Bound in the Phase Retrieval Problem</i> Radu Balan & David Bekkerman
A9 Amphi 1	11.20-11.45 <i>Stability of the Phase Retrieval Problem</i> Palina Salanevich
A9 Amphi 1	11.45-12.10 <i>PhasePack: A Phase Retrieval Library</i> Tom Goldstein, Christoph Studer & Rohan Chandra
14:00-19:00 Excursion to St Émilion	



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Non-Euclidean signal processing Chair: Elena Lebedeva		
A9 Amphli 2	10.05-10.30	<i>Generalized Sampling on Graphs With A Subspace Prior</i> Yuichi Tanaka & Yonina C. Eldar
	10.30-10.55	<i>Numerical computation of eigenspaces of spatio-spectral limiting on hypercubes</i> Joseph Lakey & Jeffrey Hogan
	10.55-11.20	<i>On the Transferability of Spectral Graph Filters</i> Ron Levie, Elvin Isufi & Gitta Kutyniok
	11.20-11.45	<i>Sampling on Hyperbolic Surfaces</i> Stephen D. Casey
	11.45-12.10	<i>Random Sampling for Bandlimited Signals on Product Graphs</i> Rohan Varma & Jelena Kovačević
14:00-19:00 Excursion to St Émilion		



Approximation by crystal invariant subspaces

Ursula Molter (U. Buenos Aires, Argentina)

Abstract: In this talk we will look at approximation properties of spaces invariant under the action of a crystal group. We show how to characterize these spaces by a property of the range function. Using this fact and the results for shift invariant spaces, we show how to solve the following problem: Let $\mathcal{F} := \{f_1, \dots, f_m\}$ (the data) be given vectors of a Hilbert space \mathcal{H} . Which is the crystal invariant subspace $S \subset \mathcal{H}$ of k generators that minimizes the error to the data, in the sense that

$$\sum_{i=1}^m \|f_i - P_S(f_i)\|^2$$

is minimal, where P_S is the orthogonal projection onto S . This provides a rotational invariant model for images.



Phase Retrieval (invited session)

Chair: Tom Goldstein & Irène Waldspurger

10.05-10.30: 3D Phaseless Imaging at Nano-scale: Challenges and Possible Solutions

Mahdi Soltanolkotabi

Abstract: In a variety of scientific applications we are interested in imaging 3D objects at very fine resolutions. However, we typically can not measure the object or its footprint directly. Rather restricted by fundamental laws governing the propagation of light we have access to 2D magnitude-only measurements of the 3D dimensional object through highly nonlinear projection mappings. Therefore, reconstructing the object requires inverting highly nonlinear and seemingly non-invertible mappings. In this paper we discuss some of the challenges that arises in such three dimensional phaseless imaging problems and offer possible solutions for 3D reconstruction. In particular we demonstrate how variants of the recently proposed Accelerated Wirtinger Flow (AWF) algorithm can enable precise 3D reconstruction at unprecedented resolutions.

10.30-10.55: Optimally Sample-Efficient Phase Retrieval with Deep Generative Models

Oscar Leong, Paul Hand & Vladislav Voroninski

Abstract: We consider the phase retrieval problem, which asks to recover a structured $\mathbb{L} \times \mathbb{L}$ -dimensional signal from m quadratic measurements. In many imaging contexts, it is beneficial to enforce a sparsity prior on the signal to reduce the number of measurements necessary for recovery. However, the best known methodologies for sparse phase retrieval have a sub-optimal quadratic dependency on the sparsity level of the signal at hand. In this work, we instead model signals as living in the range of a deep generative neural network $G : \mathbb{R}^k \rightarrow \mathbb{R}^n$. We show that under the model of a d -layer feed forward neural network with Gaussian weights, $m = O(kd^2 \log n)$ generic measurements suffice for the ℓ^2 empirical risk minimization problem to have favorable geometry. In particular, we exhibit a descent direction for all points outside of two arbitrarily small neighborhoods of the true k -dimensional latent code and a negative reflection of it. Our proof is based on showing the sufficiency of two deterministic conditions on the generator and measurement matrices, which are satisfied with high probability under random Gaussian ensembles. We corroborate these results with numerical experiments showing that enforcing a generative prior via empirical risk minimization outperforms sparse phase retrieval methods.



Phase Retrieval (invited session)

Chair: Tom Goldstein & Irène Waldspurger

10.55-11.20: The Cramer-Rao Lower Bound in the Phase Retrieval Problem

Radu Balan & David Bekkerman

Abstract: This paper presents an analysis of Cramer-Rao lower bounds (CRLB) in the phase retrieval problem. Previous papers derived Fisher Information Matrices for the phaseless reconstruction setup. Two estimation setups are presented. In the first setup the global phase of the unknown signal is determined by a correlation condition with a fixed reference signal. In the second setup an oracle provides the optimal global phase. The CRLB is derived for each of the two approaches. Surprisingly (or maybe not) they are different.

11.20-11.45: Stability of the Phase Retrieval Problem

Palina Salanevich

Abstract: Phase retrieval is a non-convex inverse problem of signal reconstruction from intensity measurements with respect to a measurement frame. One of the main problems in phase retrieval is to determine for which frames the associated phaseless measurement map is injective and stable. In this paper we address the question of stability of phase retrieval for two classes of random measurement maps, namely, frames with independent frame vectors satisfying bounded fourth moment assumption and frames with no independence assumptions. We propose a new method based on the frame order statistics, which can be used to establish stability of the measurement maps for other classes of frames.



Phase Retrieval (invited session)

Chair: Tom Goldstein & Irène Waldspurger

11.45-12.10: PhasePack: A Phase Retrieval Library

Tom Goldstein, Christoph Studer & Rohan Chandra

Abstract: Phase retrieval deals with the estimation of complex-valued signals solely from the magnitudes of linear measurements. While there has been a recent explosion in the development of phase retrieval algorithms, the lack of a common interface has made it difficult to compare new methods against the state-of-the-art. We introduce PhasePack with the purpose of creating a common software interface for a wide range of phase retrieval algorithms and to provide a common testbed using both synthetic data and empirical imaging datasets. Using PhasePack, we examine a number of issues. Can the performance of convex relaxation methods compete with non-convex approaches? How much does initialization affect results, and which initialization methods work best? Can methods that are designed and analyzed for Gaussian random measurements be effectively applied to empirical data?



Non-Euclidean signal processing

Chair: Elena Lebedeva

10.05-10.30: Generalized Sampling on Graphs With A Subspace Prior

Yuichi Tanaka & Yonina C. Eldar

Abstract: We consider a framework for generalized sampling of graph signals that extends sampling results in shift-invariant (SI) spaces to the graph setting. We assume that the input signal lies in a periodic graph spectrum subspace, which generalizes the standard SI assumption to graph signals. Sampling is performed in the graph frequency domain by an arbitrary graph filter. We show that under a mild condition on the sampling filter, perfect recovery is possible using a correction filter that can be represented as a spectral graph filter whose response depends on the prior subspace spectrum and on the sampling filter. This filter parallels the correction filter in SI sampling in standard signal processing. Since the input space and the sampling filter are almost arbitrary, our framework allows perfect recovery of many classes of input signals from a variety of different sampling patterns using a simple correction filter. For example, our method enables perfect recovery of non-bandlimited graph signals from their bandlimited measurements.

10.30-10.55: Numerical computation of eigenspaces of spatio-spectral limiting on hypercubes

Joseph Lakey & Jeffrey Hogan

Abstract: Hypercubes are Cayley graphs of the N -fold product of the integers mod two. Spatio-spectral limiting on hypercubes refers to truncation to the path neighborhood of a vertex, followed by projection onto small eigenmodes of the graph Laplacian. We present a method to compute eigenspaces of spatio-spectral limiting on hypercubes leveraging recent work of the authors that provides a geometric identification of the eigenspaces.



Non-Euclidean signal processing

Chair: Elena Lebedeva

10.55-11.20: On the Transferability of Spectral Graph Filters

Ron Levie, Elvin Isufi & Gitta Kutyniok

Abstract: This paper focuses on spectral filters on graphs, namely filters defined as elementwise multiplication in the frequency domain of a graph. In many graph signal processing settings, it is important to transfer a filter from one graph to another. One example is in graph convolutional neural networks (ConvNets), where the dataset consists of signals defined on many different graphs, and the learned filters should generalize to signals on new graphs, not present in the training set. A necessary condition for transferability (the ability to transfer filters) is stability. Namely, given a graph filter, if we add a small perturbation to the graph, then the filter on the perturbed graph is a small perturbation of the original filter. It is a common misconception that spectral filters are not stable, and this paper aims at debunking this mistake. We introduce a space of filters, called the Cayley smoothness space, that contains the filters of state-of-the-art spectral filtering methods, and whose filters can approximate any generic spectral filter. For filters in this space, the perturbation in the filter is bounded by a constant times the perturbation in the graph, and filters in the Cayley smoothness space are thus termed linearly stable. By combining stability with the known property of equivariance, we prove that graph spectral filters are transferable.

11.20-11.45: Sampling on Hyperbolic Surfaces

Stephen D. Casey

Abstract: We discuss harmonic analysis in the setting of hyperbolic space, and then focus on sampling theory on hyperbolic surfaces. We connect sampling theory with the geometry of the signal and its domain. It is relatively easy to demonstrate this connection in Euclidean spaces, but one quickly gets into open problems when the underlying space is not Euclidean. We discuss how to extend this connection to hyperbolic geometry and general surfaces, outlining an Erlangen-type program for sampling theory.



Non-Euclidean signal processing

Chair: Elena Lebedeva

11.45-12.10: Random Sampling for Bandlimited Signals on Product Graphs

Rohan Varma & Jelena Kovačević

Abstract: In this work, we construct a structured framework for the efficient random sampling and recovery of bandlimited graph signals that lie on product graphs. Product graphs are a model to construct large complex graphs from smaller simpler building blocks we call graph atoms, and are a convenient tool to model rich classes of multi-modal graph-structured data. Our randomized sampling framework prescribes an optimal sampling distribution over the nodes of the product graph constructed by only processing these smaller graph atoms. As a result, the framework achieves significant savings in computational complexity with respect to previous works that do not exploit the inherent structure of product graphs.