

From directional statistics to applications in signal processing

Martin Ehler

University of Vienna
Faculty of Mathematics

Advances in Directional Statistics
Brussels 2014

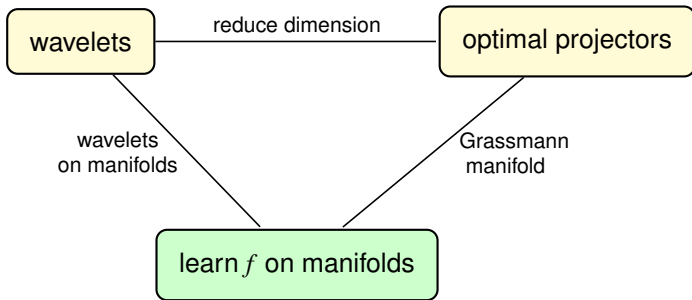
W|W|T|F

VIENNA SCIENCE
AND TECHNOLOGY FUND



universität
wien

High-dimensional harmonic analysis



eigenfunctions of Laplace-Beltrami

covering numbers

Laplacian (eigenfunctions) on manifolds

Vienna Research Group



Manuel Gräf



Monika Dörfler

2008: 3-year Fellowship at National Institutes of Health (NIH)
High-Resolution Mapping of Retinal Chromophores



2010: NIH/DFG Research Career Transition Awards Program

Developing Effective Algorithms for High-dimensional Biomedical Data and Image Analysis through Dimension Reduction Methods and Sparse Data Representations



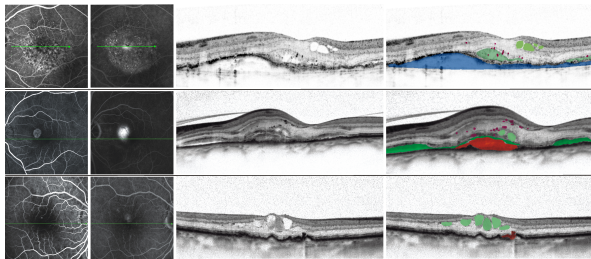
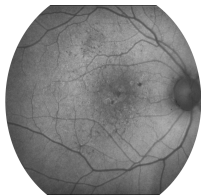
Deutsche
Forschungsgemeinschaft
DFG

2013: Wiener Wissenschafts-, Forschungs- und Technologiefonds

Vienna Research Groups for Young Investigators Call 2012 "Mathematics and ..."
Computational Harmonic Analysis of High-Dimensional Biomedical data



8-year project with the Eye Clinic Vienna



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Outline

- 1 Part I: Granular rod experiments
- 2 Main Part: filterbanks
- 3 Main Part: Modifying Tyler/Kent's M-estimators
- 4 Part III: Outlook on diffraction imaging/phase retrieval



Outline

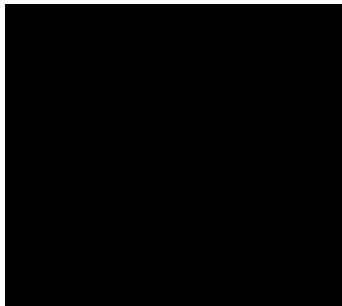
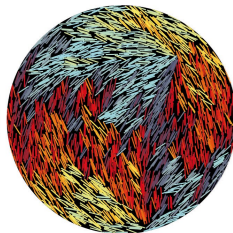
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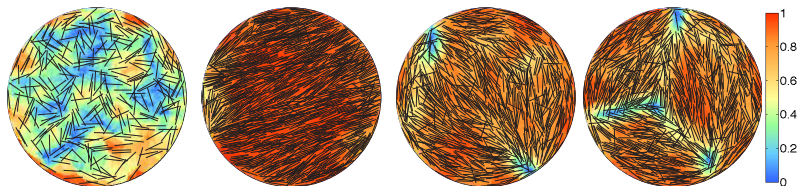


Which one is more ordered?



(Jennifer Galanis)



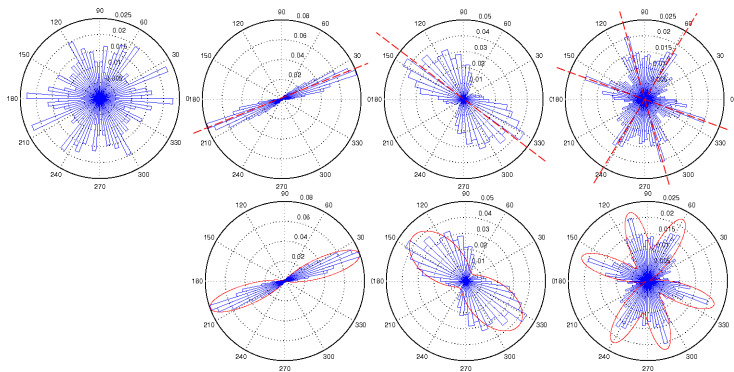


(a)

(b)

(c)

(d)



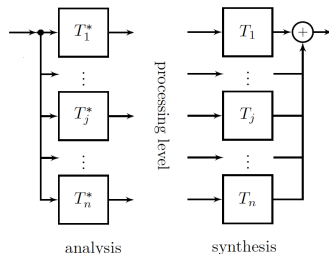
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filter bank design

Given $\{T_j\}_{j=1}^n \subset \mathbb{C}^{d \times r}$:



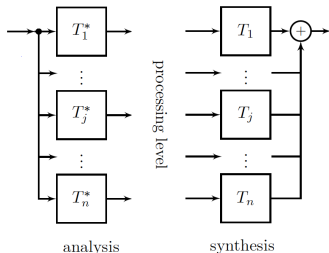
Requirements:

- perfect reconstruction: $z = \sum_{j=1}^n T_j T_j^* z, \forall z \in \mathbb{R}^d$
- equal norm: $\|T_j\|_{HS} = \|T_k\|_{HS} \quad \forall j, k$



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2 naive ideas

For “nice” $\{T_j\}_{j=1}^n \subset \mathbb{C}^{d \times r}$,

$$S = \sum_{j=1}^n T_j T_j^* \quad \text{is invertible}$$

(1) $\{S^{-1/2} T_j\}_{j=1}^n$ yields

- perfect reconstruction: $\sum_{j=1}^n S^{-1/2} T_j (S^{-1/2} T_j)^* = I$
- **not** equal norm: $\|S^{-1/2} T_j\|_{HS} \neq \|S^{-1/2} T_k\|_{HS}$ in general...

(2) $\left\{ \frac{S^{-1/2} T_j}{\|S^{-1/2} T_j\|_{HS}} \right\}_{j=1}^n$

- equal norm
- **no** perfect reconstruction: $\sum_{j=1}^n S^{-1/2} T_j (S^{-1/2} T_j)^* \neq I$ in general...

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Tyler/Kent's M-estimators

- estimating Σ of angular central Gaussian distribution

$$g_{\Sigma}(x) = \det(\Sigma)^{-1/2} (x^{\top} \Sigma^{-1} x)^{-d/2}$$

- iterative scheme: $\{x_j\}_{j=1}^n \subset \mathbb{S}^{d-1}$ i.i.d. sample from g_{Σ}

$$\Gamma_0 := \frac{1}{d} I, \quad \Gamma_{k+1} := \frac{\left(\frac{d}{n} \sum_{j=1}^n \frac{x_j x_j^*}{\|\Gamma_k^{1/2} x_j\|^2} \right)^{-1}}{\text{trace} \left(\left(\frac{d}{n} \sum_{j=1}^n \frac{x_j x_j^*}{\|\Gamma_k^{1/2} x_j\|^2} \right)^{-1} \right)}$$

converges towards $\Gamma \approx \Sigma$ (up to scaling).



Kent, Tyler: *Maximum likelihood estimation for the wrapped Cauchy distribution*, J. of Applied Statistics 15 (1988), no. 2, 247-254.



Tyler: *A distribution-free M-estimate of multivariate scatter*, Annals of Statistics 15 (1987), no. 1, 234-251.



Tyler: *Statistical analysis for the angular central Gaussian distribution*, Biometrika 74 (1987), no. 3, 579-590.

Theorem (E. '13)

For nice $\{T_j\}_{j=1}^n \subset \mathbb{C}^{d \times r}$, the recursive scheme

$$\Gamma_0 := \frac{1}{d}I, \quad \Gamma_{k+1} := \frac{\left(\frac{d}{n} \sum_{j=1}^n \frac{T_j T_j^*}{\text{trace}(T_j^* \Gamma_k T_j)}\right)^{-1}}{\text{trace}\left(\left(\frac{d}{n} \sum_{j=1}^n \frac{T_j T_j^*}{\text{trace}(T_j^* \Gamma_k T_j)}\right)^{-1}\right)}$$

converges towards $\Gamma \succeq 0$ and

$$\left\{ \frac{\Gamma^{1/2} T_j}{\|\Gamma^{1/2} T_j\|_{HS}} \right\}_{j=1}^n$$

yields *equal norm* and *perfect reconstruction*.

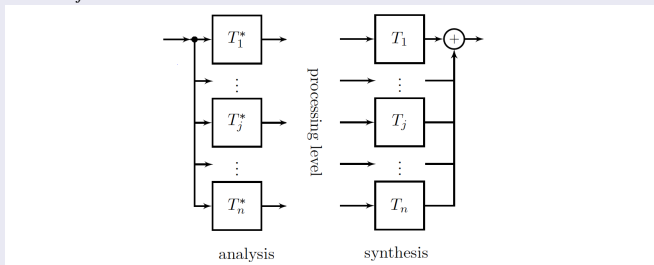


E.: Preconditioning filter bank decompositions using structured normalized tight frames, arXiv.

Isometric filter banks

Corollary (E. '13)

For nice $\{T_j\}_{j=1}^n \subset \mathbb{C}^{d \times r}$,



yields perfect reconstruction

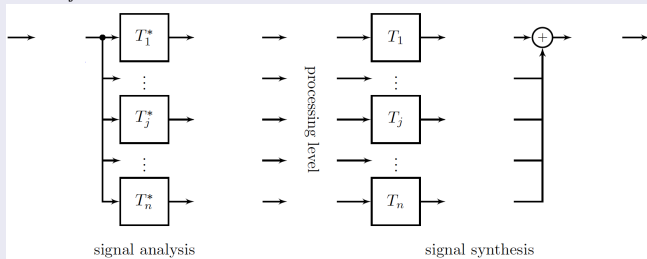


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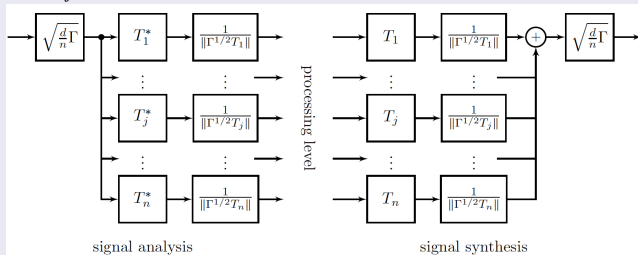


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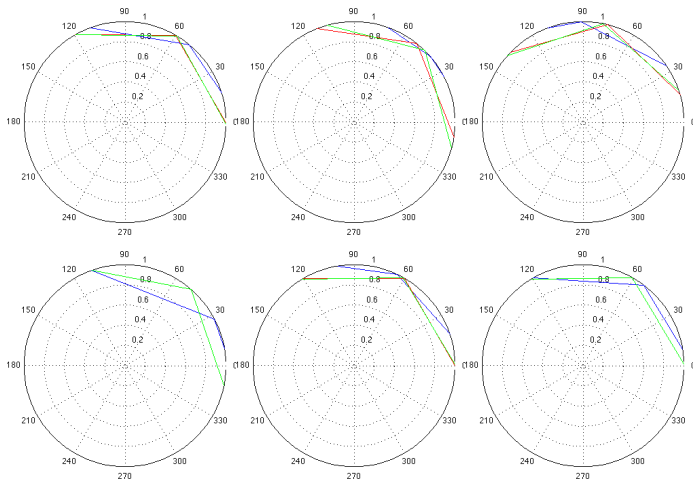
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Example

$$d = 3, r = 1$$



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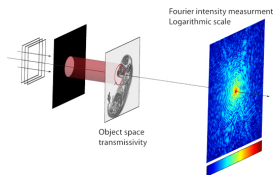
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Outlook: diffraction imaging

Let $x \in \mathbb{C}^d$ be unknown

- measure $b_1 = \|P_1 x\|^2, \dots, b_n = \|P_n x\|^2$



P_j orth. rank k projector

AIM: identify xx^*

- zonal polynomials on Grassmann manifold \mathcal{G} or, more generally,

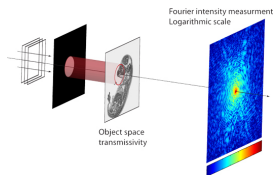
$$\mathcal{G} := \{O \operatorname{diag}(\lambda_1, \dots, \lambda_d) O^* : O \in \mathcal{O}(d)\}$$

- compute moments of “uniform” distribution on \mathcal{G}
- compute eigenfunctions of Laplacian on manifolds from the data
- spherical t -designs, Grassmannian designs, ... on \mathcal{G} , manifolds...

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Summary

- **statistical modeling**: granular rod experiments (✓)
- **covariance estimation**: filter bank design ✓
- **moments on manifolds**: phase retrieval ✓
- **shape analysis**: retinal images