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Existence and Approximations of Wavelet Uncertainty Minimizers

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September 14, 2021

Based on joint work with Ron Levie, Jan-Fredrik Olsen and Nir Sochen

Continuous wavelet transform

The wavelet transform $W_f : L^2(\mathbb{R}) \rightarrow L^2(\mathbb{R}^2, e^{-\alpha})$

$$W_f[s](\alpha, \beta) = e^{-\alpha/2} \int_{\mathbb{R}} s(t) \overline{f\left(\frac{t-\beta}{e^\alpha}\right)} dt$$

is induced by the **representation**

$$\pi(\alpha, \beta)f(t) = e^{-\alpha/2} f\left(\frac{t-\beta}{e^\alpha}\right)$$

of **time and scale shifts** in the sense that

$$W_f[s](\alpha, \beta) = \langle s, \pi(\alpha, \beta)f \rangle_{L^2}$$

Examples of wavelets



Figure: Haar

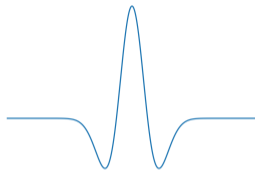


Figure: Mexican hat

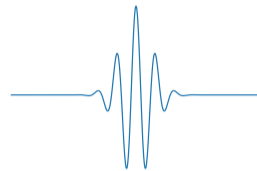


Figure: Morlet



Figure: Coiflet

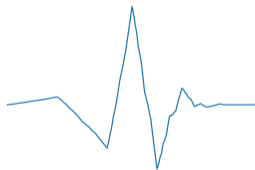


Figure: Daubechies



Figure: Symlet

An example (2 chirps)

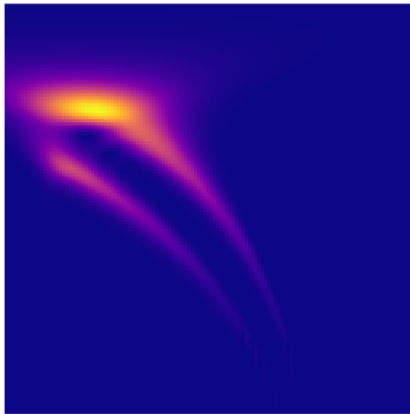


Figure: Wavelet transform of two chirps with respect to Morlet wavelet

Wavelet design

Mother wavelet f must only satisfy the **admissibility condition**

$$\int_0^{\infty} \frac{|\hat{f}(\omega)|^2}{\omega} d\omega < \infty$$

to guarantee invertibility

Wavelet design: Constructing mother wavelets f with desirable properties for the continuous wavelet transform

Wavelet uncertainty

Want wavelet transform to be well localized in \mathbb{R}^2

→ Want wavelet to be well localized in **time** and **scale**

- ▶ Historically, wavelet design has been led by qualitative features¹
- ▶ Quantitative approaches have previously been unsuccessful^{2,3}
- ▶ A framework by Levie and Sochen enables a quantitative approach⁴

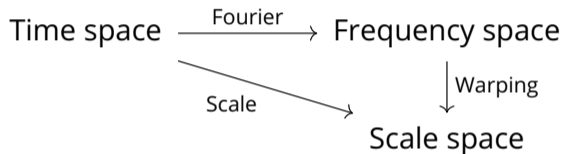
¹Daubechies, *Ten lectures on wavelets*, (1992)

²Dahlke and Maass, *The affine uncertainty principle in one and two dimensions*, (1995)

³Maass et al, *Do uncertainty minimizers attain minimal uncertainty?*, (2010)

⁴Levie and Sochen, *Uncertainty principles and optimally sparse wavelet transforms*, (2020)

To talk about scale, we introduce **scale space**:



Elements of the scale space are denoted as \tilde{f} ,

$$\tilde{f}(\sigma) = e^{-\sigma/2} \hat{f}(e^{-\sigma})$$

Localization

To measure how localized a wavelet is in time and scale, we introduce the **observables**:

$$T_x : f(t) \mapsto tf(t), \quad \tilde{T}_\sigma : \tilde{f}(\sigma) \mapsto \sigma \tilde{f}(\sigma)$$

We measure localization with **expected value** and **variance**:

$$e_f(T) = \langle Tf, f \rangle, \quad v_f(T) = \langle (T - e_f(T))^2 f, f \rangle$$

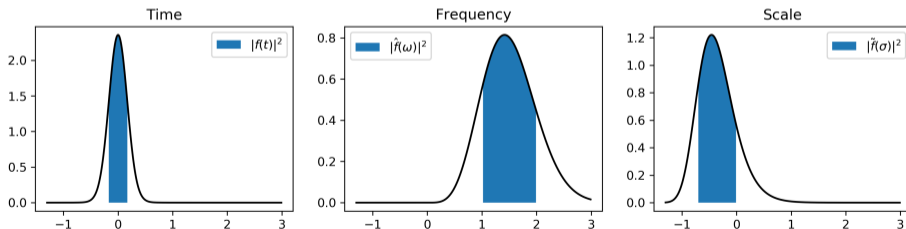


Figure: The complex Mexican hat wavelet

The observables T_x, T_σ are canonical (wrt. π) in the sense that

$$e_{\pi(0,\beta)f}(T_x) = e_f(T_x) + \beta,$$

$$e_{\pi(\alpha,0)f}(T_\sigma) = e_f(T_\sigma) + \alpha$$

Signal space uncertainty

Makes sense to define uncertainty as variance of properties we measure

$$\mathcal{L}_S(f) := e^{-2e_f(T_\sigma)} v_f(T_x) + v_f(T_\sigma)$$

- ▶ Want **invariance** $\mathcal{L}_S(f) = \mathcal{L}_S(\pi(\alpha, \beta)f)$

Lemma

If $e_f(T_x) = e_f(T_\sigma) = 0$,

$$\mathcal{L}_S(f) = \|T_x f\|^2 + \|T_\sigma f\|^2$$

Phase space uncertainty

The **phase space uncertainty** was introduced by Levie, Avraham and Sochen via the ambiguity function $K_f(\alpha, \beta) = \langle f, \pi(\alpha, \beta)f \rangle$

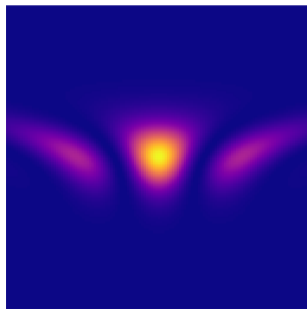
Related to the “blurriness” of the wavelet transform by

$$Q \in W_f[L^2] \implies Q = K_f * Q$$

Related observables are:

$$A : F(\alpha, \beta) \mapsto \alpha F(\alpha, \beta),$$

$$B : F(\alpha, \beta) \mapsto \beta F(\alpha, \beta)$$



Phase space uncertainty

Definition

$$\mathcal{L}_P(f) = v_{K_f}(A) + v_{K_f}(B)$$

Using wavelet-Plancherel theory⁵:

Theorem

If $e_f(T_x) = e_f(T_\sigma) = 0$,

$$\mathcal{L}_P(f) = \underbrace{\|T_x f\|^2 + \|T_\sigma f\|^2}_{\text{from } \mathcal{L}_S(f)} + v_{\frac{\hat{f}}{\|\hat{f}\|_{\mathcal{W}}}}^{\mathcal{W}} \left(i\omega \frac{\partial}{\partial \omega} \right) \left\| \frac{\hat{f}}{\omega} \right\|^2 + v_{\frac{\hat{f}}{\|\hat{f}\|_{\mathcal{W}}}}^{\mathcal{W}} (-\ln(\omega))$$

⁵Levie and Sochen, *A wavelet plancherel theory with application to sparse continuous wavelet transform*, (2017)

Theorem

Let \mathcal{L} be one of \mathcal{L}_S and \mathcal{L}_P . Then there exists an $f \in L^2$ with $e_f(T_x) = e_f(T_\sigma) = 0$ such that

$$\mathcal{L}(f) = \inf_{y \in \mathcal{D}} \mathcal{L}(y)$$

where \mathcal{D} is the domain of \mathcal{L}

Sketch of proof of existence

Consider a minimizing sequence $(f_n)_n \subset \mathcal{D}_S$ (with $e_{f_n}(T_x) = e_{f_n}(T_\sigma) = 0$)
i.e.

$$\mathcal{L}_S(f_n) \xrightarrow{n \rightarrow \infty} \inf_{y \in \mathcal{D}_S} \mathcal{L}_S(y)$$

For large enough n , $f_n \in \mathcal{K}$ where

$$\mathcal{K} = \left\{ f \in \mathcal{D}_S : \|T_x f\|^2 \leq K, \|T_\sigma f\|^2 \leq K \right\}$$

for some constant K

Strategy:

\mathcal{K} compact \implies existence of a minimizer

Sketch of proof of existence

Goal: Show \mathcal{K} compact

\mathcal{K} closed:

Write \mathcal{K} as intersection of closed subsets.

$$\begin{aligned} &\{e_f(T_x) = 0, \|T_x f\|^2 \leq K\} \\ &\{e_f(T_\sigma) = 0, \|T_\sigma f\|^2 \leq K\} \end{aligned}$$

\mathcal{K} pre-compact:

Lemma

For any $\varepsilon > 0$, there exists a compact subset $C_{a,b}$ of L^2 such that for any $f \in \mathcal{K}$, there is a $y \in C_{a,b}$ such that

$$\|f - y\| < \varepsilon.$$

Lemma \implies any sequence in \mathcal{K} has a Cauchy subsequence

L^2 complete $\implies \mathcal{K}$ pre-compact



Smoothness properties

Theorem

If f is a minimizer of \mathcal{L}_S with $e_f(T_x), e_f(T_\sigma) = 0$, then $f \in C^\infty$ and

$$f''(\omega) = \left(\ln(\omega)^2 + \kappa \ln(\omega) - \sigma \right) f(\omega)$$

where

$$\kappa = 2\|f'\|^2,$$

$$\sigma = \|f'\|^2 + \|\ln(\omega)f\|^2$$

Why do we need to approximate?

We can only optimize functions in finite dimensional spaces

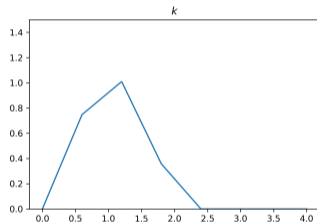
→ **Space of linear splines** with spacing h

$$P_h(0, b) \subset L^2(0, b)$$

We want to verify:

$$\inf_{y \in P_h(0, b)} \mathcal{L}(y) \xrightarrow[b \rightarrow \infty]{h \rightarrow 0} \inf_{y \in \mathcal{D}} \mathcal{L}(y),$$

$$\operatorname{argmin}_{y \in P_h(0, b)} \mathcal{L}(y) \xrightarrow[b \rightarrow \infty]{h \rightarrow 0} \operatorname{argmin}_{y \in \mathcal{D}} \mathcal{L}(y)$$



Constructing approximations

"Limits of $P_h(0, b)$ minimizers are L^2 minimizers"

Theorem

Let \mathcal{M}_h^b be the set of minimizers of \mathcal{L} in $\mathcal{D}_{\mathcal{L}} \cap P_h(0, b)$. Then any element of

$$\left\{ f \in L^2(\mathbb{R}^+) \mid \exists \text{ two sequences } b_n \rightarrow \infty, h_n \rightarrow 0 \right. \\ \left. \text{and } \exists \{p_{h_n}^{b_n} \in \mathcal{M}_{h_n}^{b_n}\}_n \text{ s.t. } f = \lim_{n \rightarrow \infty} p_{h_n}^{b_n} \right\}$$

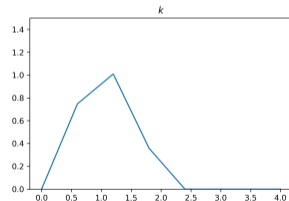
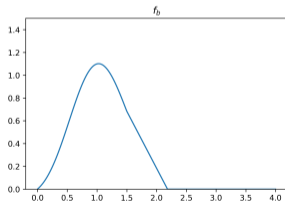
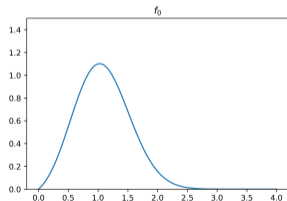
is a minimizer of \mathcal{L} in $\mathcal{D}_{\mathcal{L}}$

Constructing approximations

Lemma

Let f be a minimizer of \mathcal{L} . Then for any $\varepsilon > 0$, there exist $b > 1$, $h > 0$ and $y \in P_h(0, b)$ such that

$$\|f - y\| < \varepsilon, \quad |\mathcal{L}(f) - \mathcal{L}(y)| < \varepsilon$$



Phase space uncertainty minimizers

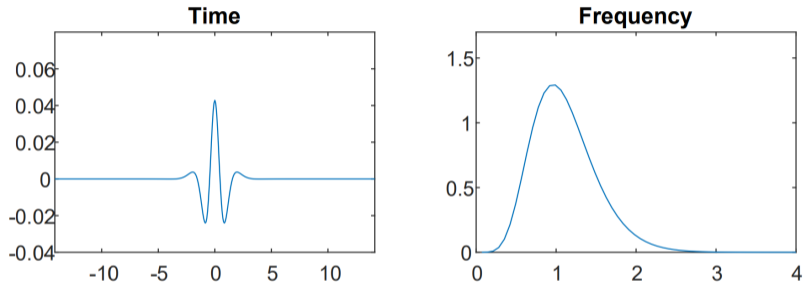


Figure: Numerical spline minimizer of \mathcal{L}_P

R. Levie, E. K. Avraham, and N. Sochen, *Wavelet design with optimally localized ambiguity function: a variational approach*, (2021)



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Thank you!
Questions?