

## Stability estimates for the inversion of the truncated Hilbert transform

Reema Al Aifari and Michel Defrise, Vrije Universiteit Brussel  
Alexander Katsevich, University of Central Florida

- ▶ Context: limited data reconstruction via the differentiated backprojection (DBP).
- ▶ Background: asymptotic behaviour of the SVD of the truncated Hilbert transform.
- ▶ Stability estimates for the inversion.

## Limited data reconstruction via the differentiated backprojection (DBP)

Consider the 2D Radon transform of a smooth function  $f$ , with the usual parallel beam parameterization

$$g(s, \phi) = (\mathcal{R}f)(s, \phi) = \int dl f(s u^\perp(\phi) + l u(\phi)) \quad ; \quad u(\phi) = (-\sin \phi, \cos \phi)$$

and the backprojection of its radial derivative over a 180 degree interval:

$$b(\mathbf{x} = (x, y)) = \int_0^\pi d\phi \left\{ \frac{\partial g(s, \phi)}{\partial s} \right\}_{s=\mathbf{x} \cdot \mathbf{u}^\perp(\phi)}$$

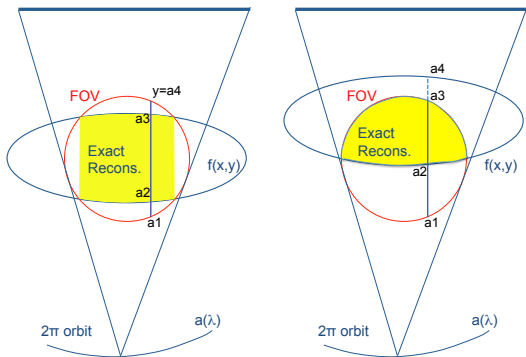
Then one has the fundamental DBP relation

$$b(x, y) = (H_{1y} f)(x, y) = \frac{1}{\pi} p.v. \int_{-\infty}^{\infty} dy' \frac{f(x, y')}{y - y'}$$

$$b(\mathbf{x} = (x, y)) = \int_0^\pi d\phi \left\{ \frac{\partial g(s, \phi)}{\partial s} \right\}_{s=\mathbf{x} \cdot \mathbf{u}^\perp(\phi)}$$

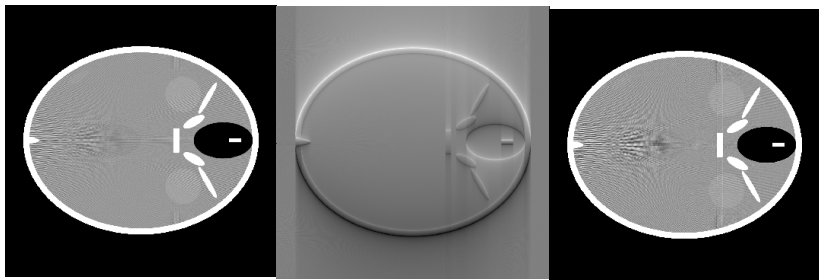
$$b(x, y) = (H_{1_y} f)(x, y) = \frac{1}{\pi} p.v. \int_{-\infty}^{\infty} dy' \frac{f(x, y')}{y - y'}$$

- ▶ Similar results for fan-beam data and for cone-beam data.
- ▶ Reduces 2D or 3D problem to a family of 1D inversions of the Hilbert transform.
- ▶ Gelfand and Graev 1991, Finch 2002, Zou et al 2004, Noo et al 2005.
- ▶ Allows accurate reconstruction from limited tomographic data sets.
- ▶ Generalization: DBP over interval less than 180 degrees  $\rightarrow$  sum of two Hilbert transforms.



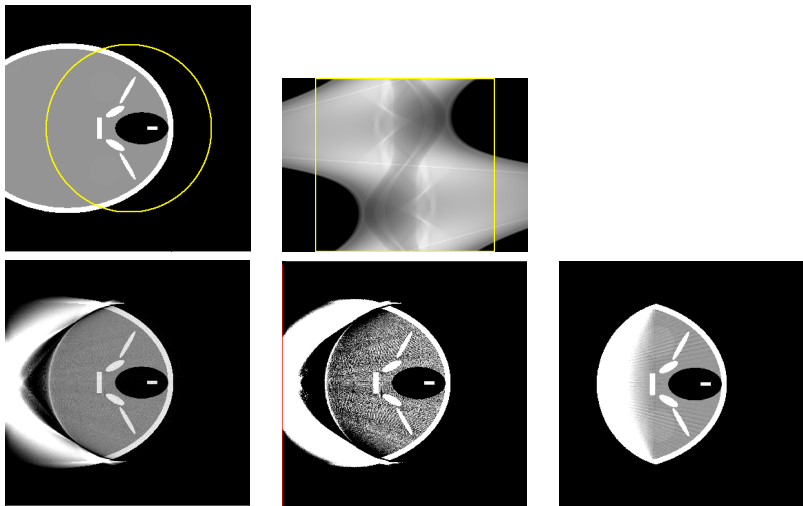
The limited data allow calculating the DBP within FOV.

- ▶ Left:  $\text{supp}(f) = (a_2, a_3) \subset \text{FOV} = (a_1, a_4) \Rightarrow$  closed form inversion of the *finite Hilbert transform* (Tricomi etc..)
- ▶ Right:  $\text{supp}(f) = (a_2, a_4)$  overlaps with the  $\text{FOV} = (a_1, a_3)$ : no closed form inversion but uniqueness and stability within part of the FOV (Defrise, Noo, Clackdoyle, Kudo 2006), *Truncated Hilbert transform*.



Example with full noise-free data. Left: FBP reconstruction. Center: the DBP. Right: inverse finite Hilbert transform along each line  $x = \text{cst}$ . Grey scale: 0.9, 1.15.

- ▶ The stability for noise is similar to FBP: same backprojection, and filters have same behaviour :  $|\nu| = |i\nu|$ .



Truncated data. Top left: Shifted phantom and FOV. Top right: fan-beam sinogram and FOV. Bottom: SART reconstruction, 200 iterations,  $\alpha = 0.25$ . Left: scale (0, 2). Center: scale (0.9, 1.15). Right: inverse finite Hilbert transform along each line  $x = \text{cst}$ . Grey scale: 0.9, 1.15

## Why is the SVD important ?

The generalized solution of a linear inverse problem  $g = Hf$  is

$$f^\dagger = \sum_n \frac{\langle g_n, g \rangle}{\sigma_n} f_n$$

with  $g_n, f_n, \sigma_n$  the SVD of the operator (or matrix)  $H$ :

$$\begin{aligned} Hf_n &= \sigma_n g_n \\ H^* g_n &= \sigma_n f_n \end{aligned}$$

- ▶ Context: limited data reconstruction via the differentiated backprojection (DBP).
- ▶ *Background: asymptotic behaviour of the SVD of the truncated Hilbert transform.*
- ▶ Stability estimates for the inversion.



## SVD of the finite Hilbert transform $(a_1 = a_2 = -1, a_3 = a_4 = 1)$ .

!! From now on,  $f(x)$  is a 1D function !!

Consider  $H_F : L_w^2(-1, 1) \rightarrow L_w^2(-1, 1)$ , with weighted norm  $\|f\|^2 = \int_{-1}^1 dy |f(y)|^2 w(y)$  with  $w(y) = 1/\sqrt{1-y^2}$ :

$$(H_F f)(x) = \frac{1}{\pi} p.v. \int_{-1}^1 \frac{f(y) dy}{y-x} \quad -1 \leq x \leq 1 \quad (1)$$

The singular system is well-known (Tricomi):

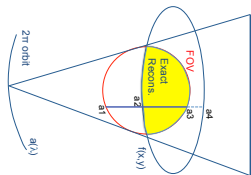
- ▶  $\sigma_n = 1, n = 0, 1, 2, \dots$
- ▶  $f_n(x) = \sqrt{2/\pi} \sqrt{1-y^2} U_n(x)$
- ▶  $g_n(x) = -\sqrt{2/\pi} T_{n+1}(x)$
- ▶  $H_F f_n = \sigma_n g_n, H_F^* g_n = \sigma_n f_n, n = 0, 1, 2, \dots, \text{ and } H_F^* T_0 = 0$

with  $U_n, T_n$  the Chebyshev polynomials:  $T_n(x) = \cos n\theta$  ;  $U_n(x) = \frac{\sin((n+1)\theta)}{\sin \theta}$  with  $x = \cos \theta$

## Asymptotic of the SVD of the truncated Hilbert transform.

Consider the truncated Hilbert problem for  $H_T : L^2(\mathcal{F}) \rightarrow L^2(\mathcal{G})$ , with  $\mathcal{F} = (a_2, a_4)$ ,  $\mathcal{G} = (a_1, a_3)$ , and  $a_1 < a_2 < a_3 < a_4$ :

$$(H_T f)(x) = \frac{1}{\pi} p.v. \int_{a_2}^{a_4} \frac{f(y) dy}{y - x} \quad a_1 \leq x \leq a_3$$



SVD:  $g_n \in L^2(a_1, a_3)$ ,  $f_n \in L^2(a_2, a_4)$  and  $H_T f_n = \sigma_n g_n$  for  $n \in \mathbb{Z}$ ,  $\sigma_n \geq \sigma_{n+1}$ .

- ▶ Spectral properties: Al-Aifari and Katsevich (SIAM Math Anal 2014)
- ▶ Asymptotic (for  $n \rightarrow \pm\infty$ ): Al-Aifari, MD, Katsevich submitted.
- ▶ Technique used by Katsevich (Inv Prob 2010, 2011) and Katsevich and Tobvis (Inv Prob 2012) for the *interior Hilbert transform* where  $\mathcal{G} \subset \mathcal{F}$ .

## Main tools

- ▶ A 2nd order differential operator  $L$  which commutes with  $H_T$  and hence has the same singular functions.
- ▶ The characterization of the behaviour of the solutions of  $Lf = \lambda f$ ,  $\lambda \in \mathbb{C}$  for  $x \rightarrow a_j^\pm$
- ▶ The WKB asymptotic form of these solutions for large  $|\lambda|$ , and the asymptotic form as  $x \rightarrow a_j^\pm$ .
- ▶ Characterization of the behaviour of  $f_n$  and  $g_n$  for  $x \rightarrow a_j^\pm$
- ▶ Enforcing these conditions restricts the values of  $\lambda$  to a countable set.

Similar approaches used for the Slepian-Pollack problem (extrapolation of band-limited signals, 1960's), the limited-angle Radon transform (Davison and Grunbaum 1980), and the finite Laplace transform (Bertero, Grunbaum, Rebolla 1986).

The differential operator,

$$L(x, d_x)\psi(x) := (P(x)\psi'(x))' + 2(x - \mu)^2\psi(x)$$

where  $P(x) = \prod_{j=1}^4 (x - a_j)$  and  $\mu = \frac{1}{4} \sum_{j=1}^4 a_j$  commutes with  $H_T$ .

$\Rightarrow H_T^* H_T$  and  $L$  have the same singular functions.

•  $a_1, a_2, a_3, a_4$  are regular singular points  $\Rightarrow$  for any  $\lambda \in \mathbb{C}$  the solutions to  $(L - \lambda)\psi = 0$  in a neighborhood of  $a_i^+$  or  $a_i^-$  are linear combinations of

$$\psi_1(x) = \sum_{j=0}^{\infty} b_j (x - a_i)^j$$

$$\psi_2(x) = \sum_{j=0}^{\infty} d_j (x - a_i)^j + \ln|x - a_i| \psi_1(x)$$

**What can be said of the behaviour of the singular functions**  
 $f_n \in L^2(a_2, a_4)$  **and**  $g_n \in L^2(a_1, a_3)$  **of**  $H_T$  ?

First note that if  $f_n$  is bounded at  $a_2$ , then

$$\begin{aligned}(H_T f_n)(x) &= \frac{1}{\pi} p.v. \int_{a_2}^{a_4} \frac{f_n(y) dy}{y - x} \\ &= \frac{1}{\pi} p.v. \int_{a_2}^{a_4} \frac{(f_n(y) - f_n(a_2)) dy}{y - x} + f_n(a_2) \underbrace{\frac{1}{\pi} \log \frac{|a_4 - x|}{|x - a_2|}}\end{aligned}$$

has a log singularity at  $x = a_2$ .

## What can be said of the behaviour of the singular functions

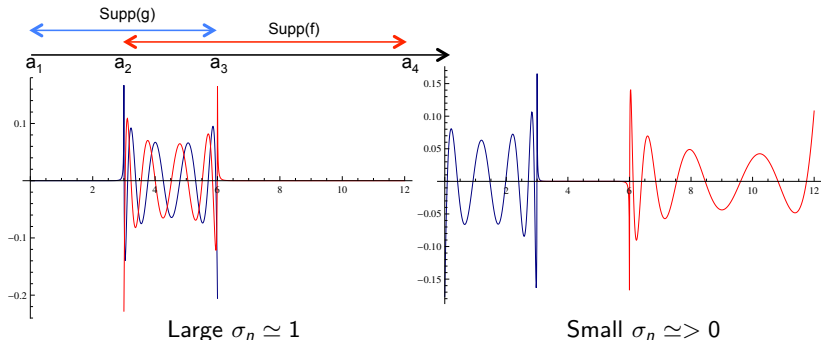
$f_n \in L^2(a_2, a_4)$  and  $g_n \in L^2(a_1, a_3)$  of  $H_T$  ?

- ▶  $f_n(x) = (1/\sigma_n)(H_T^* g_n)(x)$  is analytic outside  $(a_1, a_3) \Rightarrow f_n(x)$  bounded in  $a_4$ .
- ▶  $f_n(x)$  is bounded at  $a_2$ . Indeed if it had a log singularity at  $a_2^+$  then  $g_n(x) = (1/\sigma_n)(H_T f_n)(x)$  would not be bounded or have a log singularity there.
- ▶  $f_n(x)$  being bounded at  $a_2$ ,  $g_n(x) = (1/\sigma_n)(H_T f_n)(x)$  has a log singularity there.
- ▶ the log singularities of  $g_n$  at  $a_2^+$  and at  $a_2^-$  must be matched otherwise  $f_n(x) = (1/\sigma_n)(H_T^* g_n)(x)$  could not be bounded there

$$\Rightarrow \text{close to } a_2 \quad g_n(x) = g_{n,1}(x) + g_{n,2}(x) \log |x - a_2|$$

with  $g_{n,1}(x)$  and  $g_{n,2}(x)$  continuous.

What can be said of the behaviour of the singular functions  $f_n \in L^2(a_2, a_4)$  and  $g_n \in L^2(a_1, a_3)$  of  $H_T$  ?



Example for  $a_1 = 0, a_2 = 3, a_3 = 6, a_4 = 12$ . Blue:  $g_n$ . Red:  $f_n$ .

## Summary of the properties of $f_n$ and $g_n$

- ▶  $f_n(x)$  bounded in  $a_2$  and  $a_4$ , and log singularity in  $a_3$ .
- ▶  $g_n(x)$  bounded in  $a_1$  and  $a_3$ , and log singularity in  $a_2$
- ▶ the log singularity of  $g_n$  must be matched on  $a_2^+$  and  $a_2^-$ , idem for  $f_n$  at  $a_3$ .
- ▶  $f_n$  and  $g_n$  are solutions of  $L\phi = \lambda\phi$

⇒ Enforcing these conditions for  $\lambda$  large leads to a quantization

$$\sqrt{\lambda_n} = \frac{n\pi}{K_-} + O(n^{-1/2+\delta}) \quad n = 1, 2, 3, \dots$$

⇒ Asymptotic of the singular values obtained as (essentially)  $\|H_T f_n\|/\|f_n\|$ :

$$\sigma_n = 2e^{-n\pi K_+/K_-} (1 + O(n^{-1/2+\delta})), \quad n \rightarrow \infty.$$

with  $K_- := \int_{a_1}^{a_2} \frac{1}{\sqrt{-P(x)}} dx$  and  $K_+ := \int_{a_1}^{a_2} \frac{1}{\sqrt{-P(x)}} dx$ .

- ▶ Similar derivation for the asymptotic  $\sigma_{-n} \rightarrow 1$ .



## Details on the quantification of $\lambda$

- The WKB approximation of the solutions for large  $|\lambda|$  of the eigenequation

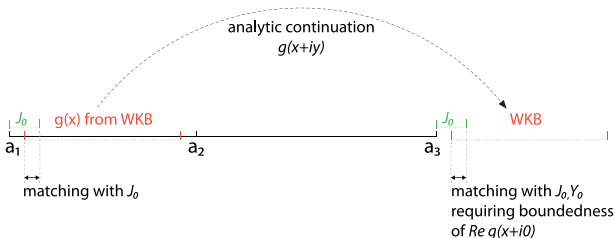
$$(L\phi)(x) - \lambda \phi(x) = (P(x)\phi'(x))' + 2(x - \mu)^2 \phi(x) - \lambda \phi(x) = 0$$

where  $P(x) = \prod_{j=1}^4 (x - a_j)$  and  $\mu = \frac{1}{4} \sum_{j=1}^4 a_j$  are linear combinations of

$$\hat{\phi}_{\pm}(z) = \frac{1}{P(z)^{1/4}} e^{\pm \sqrt{\lambda} \int_{a_1}^z \frac{d\xi}{\sqrt{P(\xi)}}} (1 + O(|\lambda|^{-\eta_1/2}))$$

with uniform accuracy in a region of  $\mathbb{C}$  excluding neighborhoods of the  $a_j$ .

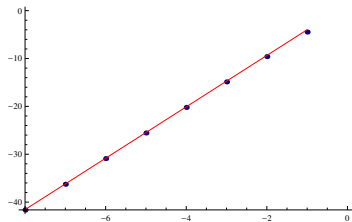
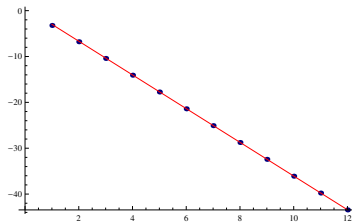
- Close to the  $a_j$  the solutions are given in terms of Bessel functions.



## Results: singular values

$$\sigma_n = 2e^{-n\pi K_+/K_-} (1 + O(n^{-1/2+\delta})) \rightarrow 0$$

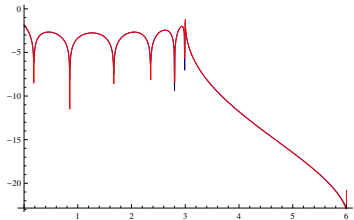
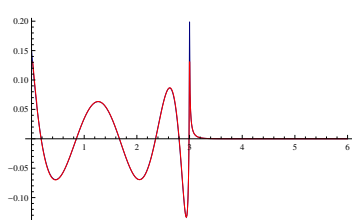
$$\sigma_{-n} = \sqrt{1 - 4e^{-2n\pi K_-/K_+} (1 + O(n^{-1/2+\delta}))} \rightarrow 1$$



$a_1 = 0, a_2 = 3, a_3 = 6, a_4 = 12$ . Logarithmic plot of the asymptotic (red line) and numerical values (blue dots) of the singular values  $\sigma_n$  tending to zero (left) and  $1 - \sigma_{-n}^2$  for the singular values  $\sigma_{-n}$  tending to 1 (right). Numerical value: Mathematica.

Conclusion: the asymptotic expressions are accurate even for small  $|n|$ .

## Results: singular functions



$a_1 = 0, a_2 = 3, a_3 = 6, a_4 = 12$ . Plot (left) and logarithmic plot (right) of the singular function  $g_6$ . Asymptotic form (red line) and numerical values (blue line). Numerical value: Mathematica.

Conclusion: the asymptotic expressions are accurate even for small  $|n|$ .

- ▶ Context: limited data reconstruction via the differentiated backprojection (DBP).
- ▶ Background: asymptotic behaviour of the SVD of the truncated Hilbert transform.
- ▶ *Stability estimates for the inversion.*

Inverse problems where  $\sigma_n$  decays exponentially to 0 are severely ill-posed and untractable in practice, they lead typically to

$$\text{reconstruction error} \simeq \frac{C}{|\log \text{noise}|}$$

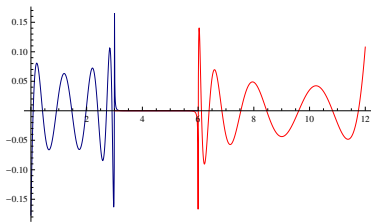
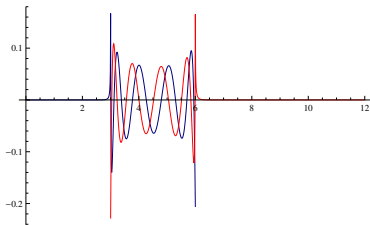
unless **very strong** prior knowledge is available (e.g. sparsity!).

Examples: backward heat equation, extrapolation of band-limited signals, etc.

Is there then any hope for the truncated Hilbert transform ?

Yes, as shown by the numerical evidence..... but Why ?

Answer: because the singular functions  $f_n$  for small  $\sigma_n$  are small within the overlap segment  $(a_2, a_3) \Rightarrow$  we expect good stability within the overlap segment, hence stable ROI reconstruction.



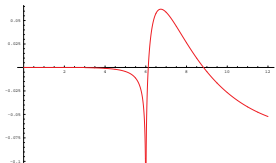
$a_1 = 0, a_2 = 3, a_3 = 6, a_4 = 12$ . Blue:  $g_n$ , red:  $f_n$ . Left: large singular value  $\sigma_n \simeq < 1$ . Right: small singular value  $\sigma_n \simeq > 0$ .

*How does the stability degrade as  $x \rightarrow a_3^-$  ?*

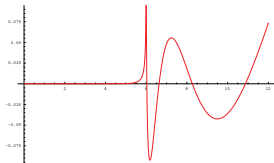
Remove a small neighborhood  $\mu > 0$  at edge of ROI and study stability on  $(a_2, a_3 - \mu)$ . We use the asymptotic of  $f_n$  to show that

$$\|f_n\|_{(a_2, a_3 - \mu)} = \left( \int_{a_2}^{a_3 - \mu} dx |f_n(x)|^2 \right)^{1/2} = \frac{1}{\sqrt{n\pi}} e^{-\beta_\mu n} (1 + O(n^{-1/2+\delta}))$$

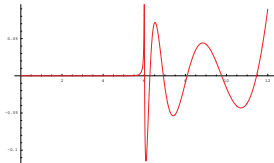
with  $\beta_\mu = \frac{\pi}{K_-} \int_{a_3 - \mu}^{a_3} \frac{dt}{\sqrt{P(t)}} \simeq \text{Cst} \sqrt{\mu}$



$$\sigma_2 = 1.13 \times 10^{-3}$$



$$\sigma_4 = 7.71 \times 10^{-7}$$



$$\sigma_6 = 5.04 \times 10^{-10}$$

Singular functions  $f_n$ . Note the decreasing amplitude within the overlap ROI  $(a_2, a_3) = (3, 6)$  where the Hilbert transform is known.

## Stability of the inversion of the truncated Hilbert transform regularized by truncated SVD.

Let

- ▶  $f_{ex} \in L^2(a_2, a_4)$  be some object, and we know that  $\|f_{ex}\| \leq E$  for some  $E$ .
- ▶  $g_{ex} = H_T f_{ex} \in L^2(a_1, a_3)$  be the noise-free data.
- ▶  $g$  be noisy data such that  $\|g - g_{ex}\| \leq \delta$  for some noise level  $\delta > 0$ .

Problem: find an estimate of  $f_{ex}$  on some interval  $a_2 \leq x \leq a_3 - \mu$ , with a small  $\mu > 0$ .

Consider the truncated SVD reconstruction  $f_M$  with cut-off index  $M$ :

$$f_M = \sum_{n=-\infty}^M \langle g, g_n \rangle \frac{1}{\sigma_n} f_n$$

The reconstruction error is

$$\begin{aligned}
 f_M - f_{ex} &= \sum_{n=-\infty}^M \langle g - g_{ex}, g_n \rangle \frac{1}{\sigma_n} f_n - \sum_{n=M+1}^{\infty} \langle g_{ex}, g_n \rangle \frac{1}{\sigma_n} f_n \\
 &= \underbrace{\sum_{n=-\infty}^M \langle g - g_{ex}, g_n \rangle \frac{1}{\sigma_n} f_n}_{\text{Statistical error}} - \underbrace{\sum_{n=M+1}^{\infty} \langle f_{ex}, f_n \rangle f_n}_{\text{Systematic error}}
 \end{aligned}$$

where we used  $\langle g_{ex}, g_n \rangle = \langle H_T f_{ex}, g_n \rangle = \langle f_{ex}, H_T^* g_n \rangle = \sigma_n \langle f_{ex}, f_n \rangle$ .  
Using the triangular inequality and all assumptions,

$$\|f_M - f_{ex}\|_{(a_2, a_3 - \mu)} \leq \delta A^{-1} e^{\alpha M} + EC_{\mu} e^{-\beta_{\mu} M}$$

with  $\alpha = \pi K_+ / K_-$  and  $\beta_{\mu} \simeq Cst \sqrt{\mu}$  the decay rates of  $\sigma_n$  and of  $\|f_n\|_{(a_2, a_3 - \mu)}$ .



$$\|f_M - f_{ex}\|_{(a_2, a_3 - \mu)} \leq \delta A^{-1} e^{\alpha M} + EC_\mu e^{-\beta_\mu M}$$

Minimize w.r.t. the SVD cut-off  $\Rightarrow M(\delta) = \frac{1}{\alpha + \beta_\mu} \log \left( \frac{EAC_\mu \beta_\mu}{\delta \alpha} \right)$

$\Rightarrow$  Stability estimate

$$\|f_{M(\delta)} - f_{ex}\|_{(a_2, a_3 - \mu)} \leq W_\mu E^{\alpha/(\beta_\mu + \alpha)} \underbrace{\delta^{\beta_\mu/(\beta_\mu + \alpha)}}_{\text{Holder continuity}} \xrightarrow{\delta \rightarrow 0} 0$$

The inversion is regularized.

## Conclusion

$$\|f_{M(\delta)} - f_{\text{ex}}\|_{(a_2, a_3 - \mu)} \leq W_\mu E^{\alpha/(\beta_\mu + \alpha)} \delta^{\beta_\mu/(\beta_\mu + \alpha)} \xrightarrow{\delta \rightarrow 0} 0$$

- ▶ Hölder continuity:  $\text{error} \simeq (\text{noise})^\eta$  typical of mildly ill-posed problems despite the exponential decay of  $\sigma_n \simeq e^{-\alpha n}$ .
- ▶ But this holds for the error within the segment  $(a_2, a_3 - \mu)$  where the Hilbert transform is known, minus some small neighborhood  $\mu$ .
- ▶ The power decreases as  $\eta = \beta_\mu/(\beta_\mu + \alpha) \sim \sqrt{\mu}$  for small  $\mu$ .
- ▶ Result obtained for TSVD but it only depends on the used prior constraint  $\|f_{\text{ex}}\| \leq E$ . Same dependence for Tikhonov regularization etc.....

## Open questions

- ▶ Stability bounds for other prior constraint, e.g.  $TV(f_{\text{ex}}) \leq E$  ? Preliminary results by Al-Aifari and Steinberger.
- ▶ Our bound is pessimistic when the ROI is far from the edge,  $a_2 < a_3 - \mu \ll a_3$ , since our  $\eta \rightarrow 1/2$  whereas one expects  $\eta \rightarrow 1$ .

Thank you !

