

# Error Estimates and Convergence Rates for Filtered Back Projection

Matthias Beckmann and Armin Iske

Department of Mathematics, University of Hamburg

IM-Workshop on  
Signals, Images, and Approximation  
March 2, 2016



Universität Hamburg

DER FORSCHUNG | DER LEHRE | DER BILDUNG

- 1 Filtered Back Projection
  - Basic Reconstruction Problem
  - Reconstruction Formula
- 2 Analysis of the Reconstruction Error in the  $L^2$ -Norm
  - $L^2$ -Error Estimate
  - Refined  $L^2$ -Error Estimate
- 3 Error Analysis for  $C^2$ -Window Functions
  - Numerical Observations
  - $L^2$ -Error Estimate for  $C^2$ -Windows
- 4 Error Analysis for  $C^k$ -Window Functions
  - $L^2$ -Error Estimate for  $C^k$ -Windows
  - Numerical Results
- 5 Asymptotic  $L^2$ -Error Estimate

# Basic Reconstruction Problem

## Problem formulation:

Let  $\Omega \subset \mathbb{R}^2$  be bounded. Reconstruct a bivariate function  $f \equiv f(x, y)$  with support  $\text{supp}(f) \subseteq \Omega$  from given Radon data

$$\{\mathcal{R}f(t, \theta) \mid t \in \mathbb{R}, \theta \in [0, \pi)\},$$

where the **Radon transform**  $\mathcal{R}f$  of  $f \in L^1(\mathbb{R}^2)$  is defined as

$$\mathcal{R}f(t, \theta) = \int_{\{x \cos(\theta) + y \sin(\theta) = t\}} f(x, y) \, dx \, dy \quad \text{for } (t, \theta) \in \mathbb{R} \times [0, \pi).$$

# Basic Reconstruction Problem

## Problem formulation:

Let  $\Omega \subset \mathbb{R}^2$  be bounded. Reconstruct a bivariate function  $f \equiv f(x, y)$  with support  $\text{supp}(f) \subseteq \Omega$  from given Radon data

$$\{\mathcal{R}f(t, \theta) \mid t \in \mathbb{R}, \theta \in [0, \pi)\},$$

where the **Radon transform**  $\mathcal{R}f$  of  $f \in L^1(\mathbb{R}^2)$  is defined as

$$\mathcal{R}f(t, \theta) = \int_{\{x \cos(\theta) + y \sin(\theta) = t\}} f(x, y) \, dx \, dy \quad \text{for } (t, \theta) \in \mathbb{R} \times [0, \pi).$$

## Analytical solution:

The inversion of  $\mathcal{R}$  involves the **back projection**  $\mathcal{B}h$  of  $h \in L^1(\mathbb{R} \times [0, \pi))$ ,

$$\mathcal{B}h(x, y) = \frac{1}{\pi} \int_0^\pi h(x \cos(\theta) + y \sin(\theta), \theta) \, d\theta \quad \text{for } (x, y) \in \mathbb{R}^2,$$

# Basic Reconstruction Problem

## Problem formulation:

Let  $\Omega \subset \mathbb{R}^2$  be bounded. Reconstruct a bivariate function  $f \equiv f(x, y)$  with support  $\text{supp}(f) \subseteq \Omega$  from given Radon data

$$\{\mathcal{R}f(t, \theta) \mid t \in \mathbb{R}, \theta \in [0, \pi)\},$$

where the **Radon transform**  $\mathcal{R}f$  of  $f \in L^1(\mathbb{R}^2)$  is defined as

$$\mathcal{R}f(t, \theta) = \int_{\{x \cos(\theta) + y \sin(\theta) = t\}} f(x, y) \, dx \, dy \quad \text{for } (t, \theta) \in \mathbb{R} \times [0, \pi).$$

## Analytical solution:

The inversion of  $\mathcal{R}$  involves the **back projection**  $\mathcal{B}h$  of  $h \in L^1(\mathbb{R} \times [0, \pi))$ ,

$$\mathcal{B}h(x, y) = \frac{1}{\pi} \int_0^\pi h(x \cos(\theta) + y \sin(\theta), \theta) \, d\theta \quad \text{for } (x, y) \in \mathbb{R}^2,$$

and is given, for  $f \in L^1(\mathbb{R}^2) \cap \mathcal{C}(\mathbb{R}^2)$ , by the **filtered back projection formula**

$$f(x, y) = \frac{1}{2} \mathcal{B} \left( \mathcal{F}^{-1} [ |S| \mathcal{F}(\mathcal{R}f)(S, \theta) ] \right) (x, y) \quad \forall (x, y) \in \mathbb{R}^2.$$

# Approximate Reconstruction

**Stabilization:** Replace the factor  $|S|$  by a **low-pass filter**  $A_L : \mathbb{R} \longrightarrow \mathbb{R}$ ,

$$A_L(S) = |S|W(s/L) = |S|W_L(S)$$

with finite bandwidth  $L > 0$  and an *even* **window function**  $W : \mathbb{R} \longrightarrow \mathbb{R}$  with compact support  $\text{supp}(W) \subseteq [-1, 1]$ .

# Approximate Reconstruction

**Stabilization:** Replace the factor  $|S|$  by a **low-pass filter**  $A_L : \mathbb{R} \longrightarrow \mathbb{R}$ ,

$$A_L(S) = |S|W(S/L) = |S|W_L(S)$$

with finite bandwidth  $L > 0$  and an *even* **window function**  $W : \mathbb{R} \longrightarrow \mathbb{R}$  with compact support  $\text{supp}(W) \subseteq [-1, 1]$ .

**Approximate reconstruction formula:**

We can express the resulting *approximate FBP reconstruction*  $f_L$  as

$$f_L = \frac{1}{2} \mathcal{B}(\mathcal{F}^{-1}A_L * \mathcal{R}f)$$

# Approximate Reconstruction

**Stabilization:** Replace the factor  $|S|$  by a **low-pass filter**  $A_L : \mathbb{R} \longrightarrow \mathbb{R}$ ,

$$A_L(S) = |S|W(S/L) = |S|W_L(S)$$

with finite bandwidth  $L > 0$  and an *even* **window function**  $W : \mathbb{R} \longrightarrow \mathbb{R}$  with compact support  $\text{supp}(W) \subseteq [-1, 1]$ .

**Approximate reconstruction formula:**

We can express the resulting *approximate FBP reconstruction*  $f_L$  as

$$f_L = \frac{1}{2} \mathcal{B} \left( \mathcal{F}^{-1} A_L * \mathcal{R}f \right) = f * K_L,$$



# Approximate Reconstruction

**Stabilization:** Replace the factor  $|S|$  by a **low-pass filter**  $A_L : \mathbb{R} \longrightarrow \mathbb{R}$ ,

$$A_L(S) = |S| W(S/L) = |S| W_L(S)$$

with finite bandwidth  $L > 0$  and an *even* **window function**  $W : \mathbb{R} \longrightarrow \mathbb{R}$  with compact support  $\text{supp}(W) \subseteq [-1, 1]$ .

**Approximate reconstruction formula:**

We can express the resulting *approximate FBP reconstruction*  $f_L$  as

$$f_L = \frac{1}{2} \mathcal{B} (\mathcal{F}^{-1} A_L * \mathcal{R}f) = f * K_L,$$

where we rely, for  $f \in L^1(\mathbb{R}^2)$  and  $g \in L^1(\mathbb{R} \times [0, \pi))$ , on the standard relation

$$\mathcal{B}g * f = \mathcal{B}(g * \mathcal{R}f)$$

and define the **convolution kernel**  $K_L : \mathbb{R}^2 \longrightarrow \mathbb{R}$  as

$$K_L(x, y) = \frac{1}{2} \mathcal{B} (\mathcal{F}^{-1} A_L) (x, y) \quad \text{for } (x, y) \in \mathbb{R}^2.$$

# Analysis of the Reconstruction Error

## Aim

Analyse the FBP reconstruction error

$$e_L = f - f_L$$

depending on the window function  $W$  and the bandwidth  $L > 0$ .

# Analysis of the Reconstruction Error

## Aim

Analyse the FBP reconstruction error

$$e_L = f - f_L$$

depending on the window function  $W$  and the bandwidth  $L > 0$ .

## Previous results:

- Pointwise and  $L^\infty$ -error estimates by [Munshi et al., 1991, Munshi, 1992]

# Analysis of the Reconstruction Error

## Aim

Analyse the FBP reconstruction error

$$e_L = f - f_L$$

depending on the window function  $W$  and the bandwidth  $L > 0$ .

## Previous results:

- Pointwise and  $L^\infty$ -error estimates by [Munshi et al., 1991, Munshi, 1992]
- $L^p$ -error estimates in terms of  $L^p$ -moduli of continuity by [Madych, 1990]

# Analysis of the Reconstruction Error

## Aim

Analyse the FBP reconstruction error

$$e_L = f - f_L$$

depending on the window function  $W$  and the bandwidth  $L > 0$ .

## Previous results:

- Pointwise and  $L^\infty$ -error estimates by [Munshi et al., 1991, Munshi, 1992]
- $L^p$ -error estimates in terms of  $L^p$ -moduli of continuity by [Madych, 1990]

## Definition (Sobolev space of fractional order)

The **Sobolev space**  $H^\alpha(\mathbb{R}^2)$  of fractional order  $\alpha \in \mathbb{R}$  is defined as

$$H^\alpha(\mathbb{R}^2) = \{f \in \mathcal{S}'(\mathbb{R}^2) \mid \|f\|_\alpha < \infty\},$$

where

$$\|f\|_\alpha^2 = \frac{1}{2\pi} \int_{\mathbb{R}^2} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x, y)|^2 \, dx \, dy.$$

Theorem ( $L^2$ -error estimate; see [Beckmann & Iske, 2015])

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $W \in L^\infty(\mathbb{R})$  and  $K_L \in L^1(\mathbb{R}^2)$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  is bounded above by

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \|1 - W\|_{\infty, [-1, 1]} \|f\|_{L^2(\mathbb{R}^2)} + L^{-\alpha} \|f\|_\alpha.$$



# $L^2$ -Error Analysis

Theorem ( $L^2$ -error estimate; see [Beckmann & Iske, 2015])

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $W \in L^\infty(\mathbb{R})$  and  $K_L \in L^1(\mathbb{R}^2)$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  is bounded above by

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \|1 - W\|_{\infty, [-1, 1]} \|f\|_{L^2(\mathbb{R}^2)} + L^{-\alpha} \|f\|_\alpha. \quad \square$$

Theorem (Convergence in the  $L^p$ -norm, see [Madych, 1990])

Let the convolution kernel  $K_L : \mathbb{R}^2 \rightarrow \mathbb{R}$  satisfy  $K_L \in L^1(\mathbb{R}^2)$  with

$$\int_{\mathbb{R}} \int_{\mathbb{R}} K_L(x, y) \, dx \, dy = 1.$$

Then, for  $f \in L^p(\mathbb{R}^2)$ ,  $1 \leq p < \infty$ ,

$$\|e_L\|_{L^p(\mathbb{R}^2)} \rightarrow 0 \quad \text{for} \quad L \rightarrow \infty. \quad \square$$

# Refined Error Estimate

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  with  $\alpha > 0$ ,  $W \in L^\infty(\mathbb{R})$  and  $K_L \in L^1(\mathbb{R}^2)$ . By defining

$$W_L(x, y) = W_L(r(x, y))$$

for  $r(x, y) = \sqrt{x^2 + y^2}$  and  $(x, y) \in \mathbb{R}^2$ , we have

$$W_L(x, y) = \mathcal{F}K_L(x, y) \quad \forall (x, y) \in \mathbb{R}^2.$$



# Refined Error Estimate

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  with  $\alpha > 0$ ,  $W \in L^\infty(\mathbb{R})$  and  $K_L \in L^1(\mathbb{R}^2)$ . By defining

$$W_L(x, y) = W_L(r(x, y))$$

for  $r(x, y) = \sqrt{x^2 + y^2}$  and  $(x, y) \in \mathbb{R}^2$ , we have

$$W_L(x, y) = \mathcal{F}K_L(x, y) \quad \forall (x, y) \in \mathbb{R}^2.$$

Thus, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  can be written as

$$\|e_L\|_{L^2}^2 = \|f - f * K_L\|_{L^2}^2 = \frac{1}{2\pi} \|\mathcal{F}f - \mathcal{F}f \cdot \mathcal{F}K_L\|_{L^2}^2 = \frac{1}{2\pi} \|\mathcal{F}f - W_L \cdot \mathcal{F}f\|_{L^2}^2$$

# Refined Error Estimate

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  with  $\alpha > 0$ ,  $W \in L^\infty(\mathbb{R})$  and  $K_L \in L^1(\mathbb{R}^2)$ . By defining

$$W_L(x, y) = W_L(r(x, y))$$

for  $r(x, y) = \sqrt{x^2 + y^2}$  and  $(x, y) \in \mathbb{R}^2$ , we have

$$W_L(x, y) = \mathcal{F}K_L(x, y) \quad \forall (x, y) \in \mathbb{R}^2.$$

Thus, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  can be written as

$$\begin{aligned} \|e_L\|_{L^2}^2 &= \|f - f * K_L\|_{L^2}^2 = \frac{1}{2\pi} \|\mathcal{F}f - \mathcal{F}f \cdot \mathcal{F}K_L\|_{L^2}^2 = \frac{1}{2\pi} \|\mathcal{F}f - W_L \cdot \mathcal{F}f\|_{L^2}^2 \\ &= \underbrace{\frac{1}{2\pi} \int_{r \leq L} |(\mathcal{F}f - W_L \cdot \mathcal{F}f)(x, y)|^2 d(x, y)}_{=: l_1} + \underbrace{\frac{1}{2\pi} \int_{r > L} |\mathcal{F}f(x, y)|^2 d(x, y)}_{=: l_2}. \end{aligned}$$

# Refined Error Estimate

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  with  $\alpha > 0$ ,  $W \in L^\infty(\mathbb{R})$  and  $K_L \in L^1(\mathbb{R}^2)$ . By defining

$$W_L(x, y) = W_L(r(x, y))$$

for  $r(x, y) = \sqrt{x^2 + y^2}$  and  $(x, y) \in \mathbb{R}^2$ , we have

$$W_L(x, y) = \mathcal{F}K_L(x, y) \quad \forall (x, y) \in \mathbb{R}^2.$$

Thus, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  can be written as

$$\begin{aligned} \|e_L\|_{L^2}^2 &= \|f - f * K_L\|_{L^2}^2 = \frac{1}{2\pi} \|\mathcal{F}f - \mathcal{F}f \cdot \mathcal{F}K_L\|_{L^2}^2 = \frac{1}{2\pi} \|\mathcal{F}f - W_L \cdot \mathcal{F}f\|_{L^2}^2 \\ &= \underbrace{\frac{1}{2\pi} \int_{r \leq L} |(\mathcal{F}f - W_L \cdot \mathcal{F}f)(x, y)|^2 d(x, y)}_{=: I_1} + \underbrace{\frac{1}{2\pi} \int_{r > L} |\mathcal{F}f(x, y)|^2 d(x, y)}_{=: I_2}. \end{aligned}$$

The integral  $I_2$  is bounded above by

$$I_2 \leq \frac{1}{2\pi} \int_{r(x, y) > L} (1 + x^2 + y^2)^\alpha L^{-2\alpha} |\mathcal{F}f(x, y)|^2 d(x, y) \leq L^{-2\alpha} \|f\|_\alpha^2.$$

# Refined Error Estimate

The integral  $I_1$  can be written as

$$I_1 = \frac{1}{2\pi} \int_{r(x,y) \leq L} \frac{|1 - W_L(x,y)|^2}{(1 + x^2 + y^2)^\alpha} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 \, d(x,y)$$

# Refined Error Estimate

The integral  $I_1$  can be written as

$$I_1 = \frac{1}{2\pi} \int_{r(x,y) \leq L} \frac{|1 - W_L(x,y)|^2}{(1 + x^2 + y^2)^\alpha} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y)$$

and estimated by

$$I_1 \leq \left( \sup_{S \in [-L, L]} \frac{(1 - W_L(S))^2}{(1 + S^2)^\alpha} \right) \frac{1}{2\pi} \int_{r(x,y) \leq L} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y)$$

# Refined Error Estimate

The integral  $I_1$  can be written as

$$I_1 = \frac{1}{2\pi} \int_{r(x,y) \leq L} \frac{|1 - W_L(x,y)|^2}{(1 + x^2 + y^2)^\alpha} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y)$$

and estimated by

$$\begin{aligned} I_1 &\leq \left( \sup_{S \in [-L, L]} \frac{(1 - W_L(S))^2}{(1 + S^2)^\alpha} \right) \frac{1}{2\pi} \int_{r(x,y) \leq L} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y) \\ &\leq \left( \sup_{S \in [-1, 1]} \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \right) \frac{1}{2\pi} \int_{\mathbb{R}} \int_{\mathbb{R}} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 dx dy. \end{aligned}$$

# Refined Error Estimate

The integral  $I_1$  can be written as

$$I_1 = \frac{1}{2\pi} \int_{r(x,y) \leq L} \frac{|1 - W_L(x,y)|^2}{(1 + x^2 + y^2)^\alpha} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y)$$

and estimated by

$$\begin{aligned} I_1 &\leq \left( \sup_{S \in [-L, L]} \frac{(1 - W_L(S))^2}{(1 + S^2)^\alpha} \right) \frac{1}{2\pi} \int_{r(x,y) \leq L} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y) \\ &\leq \left( \sup_{S \in [-1, 1]} \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \right) \frac{1}{2\pi} \int_{\mathbb{R}} \int_{\mathbb{R}} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 dx dy. \end{aligned}$$

For the sake of brevity, we define the function  $\Phi_{\alpha, W, L} : [-1, 1] \rightarrow \mathbb{R}$  via

$$\Phi_{\alpha, W, L}(S) = \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \quad \text{for } S \in [-1, 1]$$

# Refined Error Estimate

The integral  $I_1$  can be written as

$$I_1 = \frac{1}{2\pi} \int_{r(x,y) \leq L} \frac{|1 - W_L(x,y)|^2}{(1 + x^2 + y^2)^\alpha} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y)$$

and estimated by

$$\begin{aligned} I_1 &\leq \left( \sup_{S \in [-L, L]} \frac{(1 - W_L(S))^2}{(1 + S^2)^\alpha} \right) \frac{1}{2\pi} \int_{r(x,y) \leq L} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y) \\ &\leq \left( \sup_{S \in [-1, 1]} \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \right) \frac{1}{2\pi} \int_{\mathbb{R}} \int_{\mathbb{R}} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 dx dy. \end{aligned}$$

For the sake of brevity, we define the function  $\Phi_{\alpha, W, L} : [-1, 1] \rightarrow \mathbb{R}$  via

$$\Phi_{\alpha, W, L}(S) = \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \quad \text{for } S \in [-1, 1]$$

and obtain

$$I_1 \leq \left( \sup_{S \in [-1, 1]} \Phi_{\alpha, W, L}(S) \right) \|f\|_\alpha^2 = \Phi_{\alpha, W}(L) \|f\|_\alpha^2.$$



## Theorem (Refined $L^2$ -error estimate)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ , let  $W \in L^\infty(\mathbb{R})$  and  $K_L \in L^1(\mathbb{R}^2)$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  is bounded above by

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \left( \Phi_{\alpha, W}^{1/2}(L) + L^{-\alpha} \right) \|f\|_\alpha,$$

where

$$\Phi_{\alpha, W}(L) = \sup_{S \in [-1, 1]} \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \quad \text{for } L > 0. \quad \square$$

# Refined Error Estimate

## Theorem (Refined $L^2$ -error estimate)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ , let  $W \in L^\infty(\mathbb{R})$  and  $K_L \in L^1(\mathbb{R}^2)$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  is bounded above by

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \left( \Phi_{\alpha, W}^{1/2}(L) + L^{-\alpha} \right) \|f\|_\alpha,$$

where

$$\Phi_{\alpha, W}(L) = \sup_{S \in [-1, 1]} \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \quad \text{for } L > 0. \quad \square$$

## Theorem (Convergence of $\Phi_{\alpha, W}$ )

Let the window function  $W$  be continuous on  $[-1, 1]$  and satisfy  $W(0) = 1$ . Then, for all  $\alpha > 0$ ,

$$\Phi_{\alpha, W}(L) = \max_{S \in [-1, 1]} \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \longrightarrow 0 \quad \text{for } L \longrightarrow \infty. \quad \square$$

# Convergence of the Reconstruction Error

## Corollary ( $L^2$ -Convergence of the reconstruction error)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in \mathcal{C}([-1, 1])$  with  $W(0) = 1$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  satisfies

$$\|e_L\|_{L^2(\mathbb{R}^2)} = o(1) \quad \text{for} \quad L \longrightarrow \infty.$$



# Convergence of the Reconstruction Error

## Corollary ( $L^2$ -Convergence of the reconstruction error)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in \mathcal{C}([-1, 1])$  with  $W(0) = 1$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  satisfies

$$\|e_L\|_{L^2(\mathbb{R}^2)} = o(1) \quad \text{for } L \longrightarrow \infty.$$



Let  $S_{\alpha, W, L}^* \in [0, 1]$  denote the *smallest* maximizer of  $\Phi_{\alpha, W, L}$  on  $[0, 1]$ , i.e.,

$$\Phi_{\alpha, W}(L) = \sup_{S \in [-1, 1]} \Phi_{\alpha, W, L}(S) = \Phi_{\alpha, W, L}(S_{\alpha, W, L}^*).$$

# Convergence of the Reconstruction Error

## Corollary ( $L^2$ -Convergence of the reconstruction error)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in \mathcal{C}([-1, 1])$  with  $W(0) = 1$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  satisfies

$$\|e_L\|_{L^2(\mathbb{R}^2)} = o(1) \quad \text{for} \quad L \rightarrow \infty.$$



Let  $S_{\alpha, W, L}^* \in [0, 1]$  denote the *smallest* maximizer of  $\Phi_{\alpha, W, L}$  on  $[0, 1]$ , i.e.,

$$\Phi_{\alpha, W}(L) = \sup_{S \in [-1, 1]} \Phi_{\alpha, W, L}(S) = \Phi_{\alpha, W, L}(S_{\alpha, W, L}^*).$$

## Assumption

$S_{\alpha, W, L}^*$  is uniformly bounded away from 0, i.e., there exists a constant  $c_{\alpha, W} > 0$  such that

$$S_{\alpha, W, L}^* \geq c_{\alpha, W} \quad \forall L > 0.$$

# Convergence of the Reconstruction Error

## Corollary ( $L^2$ -Convergence of the reconstruction error)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in \mathcal{C}([-1, 1])$  with  $W(0) = 1$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  satisfies

$$\|e_L\|_{L^2(\mathbb{R}^2)} = o(1) \quad \text{for} \quad L \longrightarrow \infty.$$



Let  $S_{\alpha, W, L}^* \in [0, 1]$  denote the *smallest* maximizer of  $\Phi_{\alpha, W, L}$  on  $[0, 1]$ , i.e.,

$$\Phi_{\alpha, W}(L) = \sup_{S \in [-1, 1]} \Phi_{\alpha, W, L}(S) = \Phi_{\alpha, W, L}(S_{\alpha, W, L}^*).$$

## Assumption

$S_{\alpha, W, L}^*$  is uniformly bounded away from 0, i.e., there exists a constant  $c_{\alpha, W} > 0$  such that

$$S_{\alpha, W, L}^* \geq c_{\alpha, W} \quad \forall L > 0.$$

Under the above assumption follows that

$$\Phi_{\alpha, W}(L) \leq c_{\alpha, W}^{-2\alpha} \|1 - W\|_{\infty, [-1, 1]}^2 L^{-2\alpha} = \mathcal{O}(L^{-2\alpha}) \quad \text{for} \quad L \longrightarrow \infty.$$

## Corollary (Rate of convergence)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ , let  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in \mathcal{C}([-1, 1])$  with  $W(0) = 1$ . Further, let the above assumption be satisfied. Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  is bounded above by

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \left( c_{\alpha, W}^{-\alpha} \|1 - W\|_{\infty, [-1, 1]} + 1 \right) L^{-\alpha} \|f\|_{\alpha}.$$

Therefore,

$$\|e_L\|_{L^2(\mathbb{R}^2)} = \mathcal{O}(L^{-\alpha}) \quad \text{for } L \longrightarrow \infty,$$

i.e., the decay rate is determined by the smoothness  $\alpha$  of the target function  $f$ .  $\square$

# Order of Convergence

## Corollary (Rate of convergence)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ , let  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in \mathcal{C}([-1, 1])$  with  $W(0) = 1$ . Further, let the above assumption be satisfied. Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  is bounded above by

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \left( c_{\alpha, W}^{-\alpha} \|1 - W\|_{\infty, [-1, 1]} + 1 \right) L^{-\alpha} \|f\|_{\alpha}.$$

Therefore,

$$\|e_L\|_{L^2(\mathbb{R}^2)} = \mathcal{O}(L^{-\alpha}) \quad \text{for } L \longrightarrow \infty,$$

i.e., the decay rate is determined by the smoothness  $\alpha$  of the target function  $f$ .  $\square$

### Example:

Let the window function  $\chi_{[-1, 1]} \neq W \in \mathcal{C}([-1, 1])$  satisfy

$$W(S) = 1 \quad \forall S \in (-\varepsilon, \varepsilon)$$

with a constant  $\varepsilon > 0$ . Then, the above assumption is fulfilled with  $c_{\alpha, W} = \varepsilon$ .



# Numerical Observations

We investigate the behaviour of  $\Phi_{\alpha,W}$  numerically for the generalized Ramp filter  $A_L(S) = |S| W(S/L)$  with the window function

$$W(S) = \begin{cases} 1 & , 0 \leq |S| \leq \beta \\ \frac{1}{1-\beta} (1 - \beta\gamma - (1 - \gamma) |S|) & , \beta < |S| \leq 1 \end{cases} \quad \text{for } S \in [-1, 1]$$

with width  $\beta \in (0, 1)$  and jump height  $\gamma \in [0, 1]$ .

# Numerical Observations

We investigate the behaviour of  $\Phi_{\alpha,W}$  numerically for the generalized Ramp filter  $A_L(S) = |S| W(S/L)$  with the window function

$$W(S) = \begin{cases} 1 & , 0 \leq |S| \leq \beta \\ \frac{1}{1-\beta} (1 - \beta\gamma - (1 - \gamma)|S|) & , \beta < |S| \leq 1 \end{cases} \quad \text{for } S \in [-1, 1]$$

with width  $\beta \in (0, 1)$  and jump height  $\gamma \in [0, 1]$ .

Then, the above assumption

$$\exists c_{\alpha,W} > 0 \forall L > 0 : S_{\alpha,W,L}^* \geq c_{\alpha,W}$$

is fulfilled with the constant

$$c_{\alpha,W} = \beta.$$

# Numerical Observations

We investigate the behaviour of  $\Phi_{\alpha,W}$  numerically for the generalized Ramp filter  $A_L(S) = |S| W(S/L)$  with the window function

$$W(S) = \begin{cases} 1 & , 0 \leq |S| \leq \beta \\ \frac{1}{1-\beta} (1 - \beta\gamma - (1-\gamma)|S|) & , \beta < |S| \leq 1 \end{cases} \quad \text{for } S \in [-1, 1]$$

with width  $\beta \in (0, 1)$  and jump height  $\gamma \in [0, 1]$ .

Then, the above assumption

$$\exists c_{\alpha,W} > 0 \forall L > 0 : S_{\alpha,W,L}^* \geq c_{\alpha,W}$$

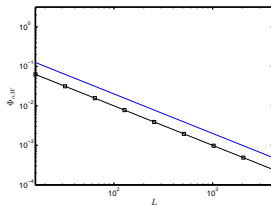
is fulfilled with the constant

$$c_{\alpha,W} = \beta.$$

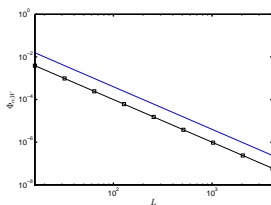
Further, for all  $\alpha > 0$ , we observe that the convergence rate of  $\Phi_{\alpha,W}$  is given by

$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2\alpha}) \quad \text{for } L \longrightarrow \infty.$$

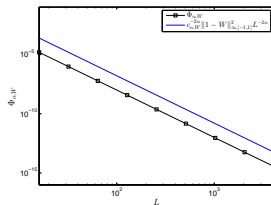
# Numerical Observations



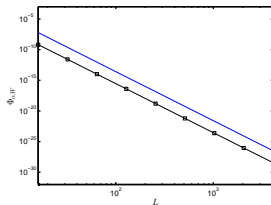
(a)  $\alpha = 0.5$



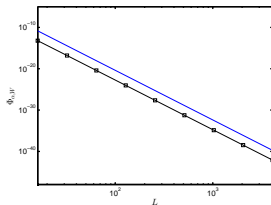
(b)  $\alpha = 1$



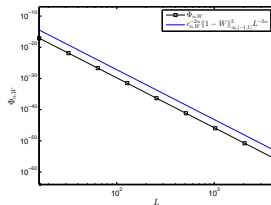
(c)  $\alpha = 2$



(d)  $\alpha = 4$



(e)  $\alpha = 6$



(f)  $\alpha = 8$

**Fig.:** Decay rate of  $\Phi_{\alpha,W}$  for the Ramp filter with width  $\beta = 0.5$  and jump height  $\gamma = 0$

# Numerical Observations

We investigate the behaviour of  $S_{\alpha,W,L}^*$  and  $\Phi_{\alpha,W}$  numerically for the following low-pass filters:

- Shepp-Logan filter:  $W(S) = \text{sinc}\left(\frac{\pi S}{2}\right) \cdot \chi_{[-1,1]}(S),$
- Cosine filter:  $W(S) = \cos\left(\frac{\pi S}{2}\right) \cdot \chi_{[-1,1]}(S),$
- Hamming filter (for  $\beta \in [\frac{1}{2}, 1]$ ):  $W(S) = (\beta + (1 - \beta) \cos(\pi S)) \cdot \chi_{[-1,1]}(S),$
- Gaussian filter (for  $\beta > 1$ ):  $W(S) = \exp\left(-(\pi S/\beta)^2\right) \cdot \chi_{[-1,1]}(S).$

# Numerical Observations

We investigate the behaviour of  $S_{\alpha,W,L}^*$  and  $\Phi_{\alpha,W}$  numerically for the following low-pass filters:

- Shepp-Logan filter:  $W(S) = \operatorname{sinc}\left(\frac{\pi S}{2}\right) \cdot \chi_{[-1,1]}(S),$
- Cosine filter:  $W(S) = \cos\left(\frac{\pi S}{2}\right) \cdot \chi_{[-1,1]}(S),$
- Hamming filter (for  $\beta \in [\frac{1}{2}, 1]$ ):  $W(S) = (\beta + (1 - \beta) \cos(\pi S)) \cdot \chi_{[-1,1]}(S),$
- Gaussian filter (for  $\beta > 1$ ):  $W(S) = \exp\left(-(\pi S/\beta)^2\right) \cdot \chi_{[-1,1]}(S).$

For  $\alpha < 2$ , we observe that the above assumption

$$\exists c_{\alpha,W} > 0 \forall L > 0 : S_{\alpha,W,L}^* \geq c_{\alpha,W}$$

is fulfilled and

$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2\alpha}) \quad \text{for} \quad L \longrightarrow \infty.$$

# Numerical Observations

We investigate the behaviour of  $S_{\alpha,W,L}^*$  and  $\Phi_{\alpha,W}$  numerically for the following low-pass filters:

- Shepp-Logan filter:  $W(S) = \text{sinc}\left(\frac{\pi S}{2}\right) \cdot \chi_{[-1,1]}(S),$
- Cosine filter:  $W(S) = \cos\left(\frac{\pi S}{2}\right) \cdot \chi_{[-1,1]}(S),$
- Hamming filter (for  $\beta \in [\frac{1}{2}, 1]$ ):  $W(S) = (\beta + (1 - \beta) \cos(\pi S)) \cdot \chi_{[-1,1]}(S),$
- Gaussian filter (for  $\beta > 1$ ):  $W(S) = \exp\left(-(\pi S/\beta)^2\right) \cdot \chi_{[-1,1]}(S).$

For  $\alpha < 2$ , we observe that the above assumption

$$\exists c_{\alpha,W} > 0 \forall L > 0 : S_{\alpha,W,L}^* \geq c_{\alpha,W}$$

is fulfilled and

$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2\alpha}) \quad \text{for} \quad L \longrightarrow \infty.$$

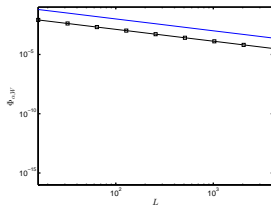
For  $\alpha \geq 2$ , we have

$$S_{\alpha,W,L}^* \longrightarrow 0 \quad \text{for} \quad L \longrightarrow \infty$$

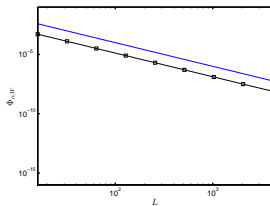
and the convergence rate of  $\Phi_{\alpha,W}$  stagnates at

$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-4}) \quad \text{for} \quad L \longrightarrow \infty.$$

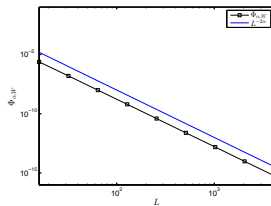
# Numerical Observations



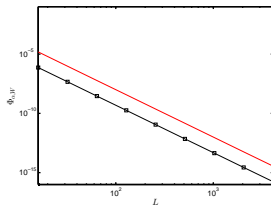
(a)  $\alpha = 0.5$



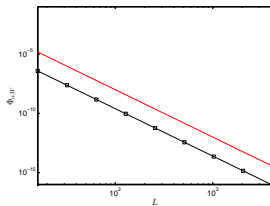
(b)  $\alpha = 1$



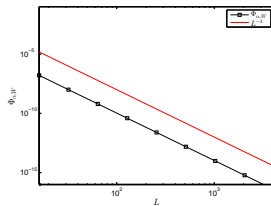
(c)  $\alpha = 2$



(d)  $\alpha = 2.5$



(e)  $\alpha = 3$



(f)  $\alpha = 4$

Fig.: Decay rate of  $\Phi_{\alpha,W}$  for the Shepp-Logan filter



## Theorem (Convergence rate of $\Phi_{\alpha,W}$ for $\mathcal{C}^2$ -windows)

Let the window function  $W$  be twice continuously differentiable on  $[-1,1]$  with  $W(0) = 1$  and let  $\alpha > 0$  be given. Then, we have

$$\Phi_{\alpha,W}(L) \leq \begin{cases} \frac{(\alpha-2)^{\alpha-2}}{\alpha^\alpha} \|W''\|_{\infty,[-1,1]}^2 L^{-4} & , \alpha > 2 \wedge L \geq \frac{\sqrt{2}}{\sqrt{\alpha-2}} \\ \frac{1}{4} \|W''\|_{\infty,[-1,1]}^2 L^{-2\alpha} & , \alpha \leq 2 \vee \left( \alpha > 2 \wedge L < \frac{\sqrt{2}}{\sqrt{\alpha-2}} \right) \end{cases}$$

for all  $L > 0$  and, especially,

$$\Phi_{\alpha,W}(L) = \mathcal{O}\left(L^{-\min\{4, 2\alpha\}}\right) \quad \text{for } L \longrightarrow \infty.$$



# Error Analysis for $\mathcal{C}^2$ -Windows

## Theorem (Convergence rate of $\Phi_{\alpha,W}$ for $\mathcal{C}^2$ -windows)

Let the window function  $W$  be twice continuously differentiable on  $[-1, 1]$  with  $W(0) = 1$  and let  $\alpha > 0$  be given. Then, we have

$$\Phi_{\alpha,W}(L) \leq \begin{cases} \frac{(\alpha-2)^{\alpha-2}}{\alpha^\alpha} \|W''\|_{\infty,[-1,1]}^2 L^{-4} & , \alpha > 2 \wedge L \geq \frac{\sqrt{2}}{\sqrt{\alpha-2}} \\ \frac{1}{4} \|W''\|_{\infty,[-1,1]}^2 L^{-2\alpha} & , \alpha \leq 2 \vee \left( \alpha > 2 \wedge L < \frac{\sqrt{2}}{\sqrt{\alpha-2}} \right) \end{cases}$$

for all  $L > 0$  and, especially,

$$\Phi_{\alpha,W}(L) = \mathcal{O}\left(L^{-\min\{4, 2\alpha\}}\right) \quad \text{for } L \rightarrow \infty.$$



### Proof:

Let  $S \in [-1, 1]$  be fixed. Because  $W$  satisfies  $W \in \mathcal{C}^2([-1, 1])$  with  $W(0) = 1$ , we can apply Taylor's theorem and obtain

$$W(S) = 1 + \frac{1}{2} W''(\xi) S^2$$

for some  $\xi$  between 0 and  $S$ , where we use  $W'(0) = 0$ , since  $W$  is even.

# Error Analysis for $\mathcal{C}^2$ -Windows

This leads to

$$\Phi_{\alpha, W, L}(S) = \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \leq \frac{\|W''\|_{\infty, [-1, 1]}^2}{4} \frac{S^4}{(1 + L^2 S^2)^\alpha}.$$

# Error Analysis for $\mathcal{C}^2$ -Windows

This leads to

$$\Phi_{\alpha,W,L}(S) = \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \leq \frac{\|W''\|_{\infty,[-1,1]}^2}{4} \frac{S^4}{(1 + L^2 S^2)^\alpha}.$$

Hence,

$$\Phi_{\alpha,W}(L) = \max_{S \in [-1,1]} \Phi_{\alpha,W,L}(S) \leq \frac{\|W''\|_{\infty,[-1,1]}^2}{4} \max_{S \in [-1,1]} \phi_{\alpha,L}(S)$$

and we now need to investigate

$$\phi_{\alpha,L}(S) = \frac{S^4}{(1 + L^2 S^2)^\alpha} \quad \text{for } S \in [-1, 1].$$

# Error Analysis for $\mathcal{C}^2$ -Windows

This leads to

$$\Phi_{\alpha,W,L}(S) = \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha} \leq \frac{\|W''\|_{\infty,[-1,1]}^2}{4} \frac{S^4}{(1 + L^2 S^2)^\alpha}.$$

Hence,

$$\Phi_{\alpha,W}(L) = \max_{S \in [-1,1]} \Phi_{\alpha,W,L}(S) \leq \frac{\|W''\|_{\infty,[-1,1]}^2}{4} \max_{S \in [-1,1]} \phi_{\alpha,L}(S)$$

and we now need to investigate

$$\phi_{\alpha,L}(S) = \frac{S^4}{(1 + L^2 S^2)^\alpha} \quad \text{for } S \in [-1, 1].$$

We can show that

$$\begin{aligned} \max_{S \in [-1,1]} \phi_{\alpha,L}(S) &= \begin{cases} \phi_{\alpha,L}(1) & , \alpha \leq 2 \vee (\alpha > 2 \wedge L < \frac{\sqrt{2}}{\sqrt{\alpha-2}}) \\ \phi_{\alpha,L}(\frac{\sqrt{2}}{L\sqrt{\alpha-2}}) & , \alpha > 2 \wedge L \geq \frac{\sqrt{2}}{\sqrt{\alpha-2}} \end{cases} \\ &\leq \begin{cases} L^{-2\alpha} & , \alpha \leq 2 \vee (\alpha > 2 \wedge L < \frac{\sqrt{2}}{\sqrt{\alpha-2}}) \\ 4 \frac{(\alpha-2)^{\alpha-2}}{\alpha^\alpha} L^{-4} & , \alpha > 2 \wedge L \geq \frac{\sqrt{2}}{\sqrt{\alpha-2}}. \end{cases} \end{aligned}$$

□

## Corollary ( $L^2$ -error estimate for $\mathcal{C}^2$ -windows)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ , let  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in \mathcal{C}^2([-1, 1])$  with  $W(0) = 1$ . Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  satisfies

$$\|e_L\|_{L^2(\mathbb{R}^2)}^2 \leq \begin{cases} \left( \frac{c_{\alpha,2}^2}{4} \|W''\|_{\infty,[-1,1]}^2 L^{-4} + L^{-2\alpha} \right) \|f\|_\alpha^2 & , \alpha > 2 \wedge L \geq L^* \\ \left( \frac{1}{4} \|W''\|_{\infty,[-1,1]}^2 L^{-2\alpha} + L^{-2\alpha} \right) \|f\|_\alpha^2 & , \alpha \leq 2 \vee (\alpha > 2 \wedge L < L^*) \end{cases}$$

with the critical bandwidth  $L^* = \frac{\sqrt{2}}{\sqrt{\alpha-2}}$  for  $\alpha > 2$  and the constant

$$c_{\alpha,2} = \frac{2}{\alpha-2} \left( \frac{\alpha-2}{\alpha} \right)^{\alpha/2},$$

which is strictly monotonically decreasing in  $\alpha > 2$ . Especially, we have

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \left( c \|W''\|_{\infty,[-1,1]} L^{-\min\{2,\alpha\}} + L^{-\alpha} \right) \|f\|_\alpha = \mathcal{O}\left(L^{-\min\{2,\alpha\}}\right). \quad \square$$

# Error Analysis for $\mathcal{C}^k$ -Windows

## Theorem (Convergence rate of $\Phi_{\alpha,W}$ for $\mathcal{C}^k$ -windows)

Let the window function  $W$  be  $k$ -times continuously differentiable on  $[-1, 1]$ ,  $k \geq 2$ , with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1$$

and let  $\alpha > 0$  be given. Then, we have

$$\Phi_{\alpha,W}(L) \leq \begin{cases} \frac{c_{\alpha,k}^2}{(k!)^2} \|W^{(k)}\|_{\infty,[-1,1]}^2 L^{-2k} & , \alpha > k \wedge L \geq L^* \\ \frac{1}{(k!)^2} \|W^{(k)}\|_{\infty,[-1,1]}^2 L^{-2\alpha} & , \alpha \leq k \vee (\alpha > k \wedge L < L^*) \end{cases}$$

with the critical bandwidth  $L^* = \frac{\sqrt{k}}{\sqrt{\alpha-k}}$  for  $\alpha > k$  and the constant

$$c_{\alpha,k} = \left(\frac{k}{\alpha-k}\right)^{k/2} \left(\frac{\alpha-k}{\alpha}\right)^{\alpha/2}.$$

*Especially,*

$$\Phi_{\alpha,W}(L) = \mathcal{O}\left(L^{-2\min\{k,\alpha\}}\right) \quad \text{for } L \longrightarrow \infty.$$



# Error Analysis for $\mathcal{C}^k$ -Windows

## Corollary ( $L^2$ -error estimate for $\mathcal{C}^k$ -windows)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ , let  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in \mathcal{C}^k([-1, 1])$ ,  $k \geq 2$ , with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1.$$

Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  satisfies

$$\|e_L\|_{L^2}^2 \leq \begin{cases} \left( \frac{c_{\alpha,k}^2}{(k!)^2} \|W^{(k)}\|_{\infty,[-1,1]}^2 L^{-2k} + L^{-2\alpha} \right) \|f\|_\alpha^2 & , \alpha > k \wedge L \geq L^* \\ \left( \frac{1}{(k!)^2} \|W^{(k)}\|_{\infty,[-1,1]}^2 L^{-2\alpha} + L^{-2\alpha} \right) \|f\|_\alpha^2 & , \alpha \leq k \vee (\alpha > k \wedge L < L^*) \end{cases}$$

and the constant

$$c_{\alpha,k} = \left( \frac{k}{\alpha - k} \right)^{k/2} \left( \frac{\alpha - k}{\alpha} \right)^{\alpha/2}$$

is strictly monotonically decreasing in  $\alpha > k$ . Especially, we have

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \left( c \|W^{(k)}\|_{\infty,[-1,1]} L^{-\min\{k,\alpha\}} + L^{-\alpha} \right) \|f\|_\alpha = \mathcal{O}\left(L^{-\min\{k,\alpha\}}\right). \quad \square$$



# Numerical Results

We investigate the behaviour of  $\Phi_{\alpha, W}$  numerically for the generalized Gaussian filter  $A_L(S) = |S| W(S/L)$  with the window function

$$W(S) = \exp\left(-\left(\frac{\pi S}{\beta}\right)^k\right) \quad \text{for } S \in [-1, 1]$$

for  $k \in \mathbb{N}_{\geq 2}$  and  $\beta > 1$ .

# Numerical Results

We investigate the behaviour of  $\Phi_{\alpha,W}$  numerically for the generalized Gaussian filter  $A_L(S) = |S| W(S/L)$  with the window function

$$W(S) = \exp\left(-\left(\frac{\pi S}{\beta}\right)^k\right) \quad \text{for } S \in [-1, 1]$$

for  $k \in \mathbb{N}_{\geq 2}$  and  $\beta > 1$ . Then,  $W$  satisfies  $W \in \mathcal{C}^k([-1, 1])$  with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1, \quad W^{(k)}(0) = -k! \left(\frac{\pi}{\beta}\right)^k \neq 0.$$

# Numerical Results

We investigate the behaviour of  $\Phi_{\alpha,W}$  numerically for the generalized Gaussian filter  $A_L(S) = |S| W(S/L)$  with the window function

$$W(S) = \exp\left(-\left(\frac{\pi S}{\beta}\right)^k\right) \quad \text{for } S \in [-1, 1]$$

for  $k \in \mathbb{N}_{\geq 2}$  and  $\beta > 1$ . Then,  $W$  satisfies  $W \in \mathcal{C}^k([-1, 1])$  with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1, \quad W^{(k)}(0) = -k! \left(\frac{\pi}{\beta}\right)^k \neq 0.$$

For  $\alpha < k$ , we observe

$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2\alpha}) \quad \text{for } L \longrightarrow \infty.$$

# Numerical Results

We investigate the behaviour of  $\Phi_{\alpha,W}$  numerically for the generalized Gaussian filter  $A_L(S) = |S| W(S/L)$  with the window function

$$W(S) = \exp\left(-\left(\frac{\pi S}{\beta}\right)^k\right) \quad \text{for } S \in [-1, 1]$$

for  $k \in \mathbb{N}_{\geq 2}$  and  $\beta > 1$ . Then,  $W$  satisfies  $W \in \mathcal{C}^k([-1, 1])$  with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1, \quad W^{(k)}(0) = -k! \left(\frac{\pi}{\beta}\right)^k \neq 0.$$

For  $\alpha < k$ , we observe

$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2\alpha}) \quad \text{for } L \longrightarrow \infty.$$

For  $\alpha \geq k$ , the convergence rate of  $\Phi_{\alpha,W}$  stagnates at

$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2k}) \quad \text{for } L \longrightarrow \infty.$$

# Numerical Results

We investigate the behaviour of  $\Phi_{\alpha,W}$  numerically for the generalized Gaussian filter  $A_L(S) = |S| W(S/L)$  with the window function

$$W(S) = \exp\left(-\left(\frac{\pi S}{\beta}\right)^k\right) \quad \text{for } S \in [-1, 1]$$

for  $k \in \mathbb{N}_{\geq 2}$  and  $\beta > 1$ . Then,  $W$  satisfies  $W \in \mathcal{C}^k([-1, 1])$  with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1, \quad W^{(k)}(0) = -k! \left(\frac{\pi}{\beta}\right)^k \neq 0.$$

For  $\alpha < k$ , we observe

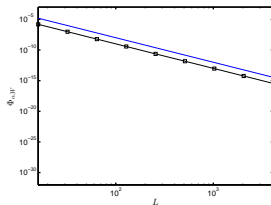
$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2\alpha}) \quad \text{for } L \longrightarrow \infty.$$

For  $\alpha \geq k$ , the convergence rate of  $\Phi_{\alpha,W}$  stagnates at

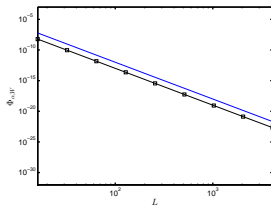
$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2k}) \quad \text{for } L \longrightarrow \infty.$$

This shows that our proven convergence order of  $\Phi_{\alpha,W}$  is optimal for  $\mathcal{C}^k$ -windows.

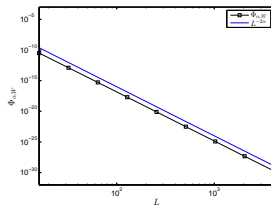
# Numerical Results



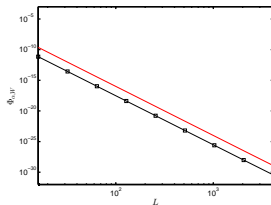
(a)  $\alpha = 2$



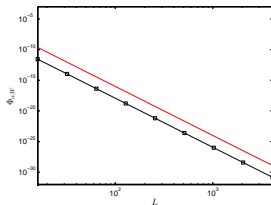
(b)  $\alpha = 3$



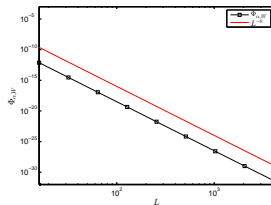
(c)  $\alpha = 4$



(d)  $\alpha = 4.5$



(e)  $\alpha = 5$



(f)  $\alpha = 6$

Fig.: Decay rate of  $\Phi_{\alpha,W}$  for the generalized Gaussian filter with  $k = 4$  and  $\beta = 4$

# Asymptotic $L^2$ -Error Estimate

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and let  $W \in L^\infty(\mathbb{R})$  be  $k$ -times differentiable at the origin,  $k \geq 2$ , with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1.$$

# Asymptotic $L^2$ -Error Estimate

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and let  $W \in L^\infty(\mathbb{R})$  be  $k$ -times differentiable at the origin,  $k \geq 2$ , with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1.$$

We again start with

$$\|e_L\|_{L^2}^2 = \underbrace{\frac{1}{2\pi} \int_{r \leq L} |(\mathcal{F}f - W_L \cdot \mathcal{F}f)(x, y)|^2 d(x, y)}_{=: l_1} + \underbrace{\frac{1}{2\pi} \int_{r > L} |\mathcal{F}f(x, y)|^2 d(x, y)}_{=: l_2}.$$



# Asymptotic $L^2$ -Error Estimate

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and let  $W \in L^\infty(\mathbb{R})$  be  $k$ -times differentiable at the origin,  $k \geq 2$ , with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1.$$

We again start with

$$\|e_L\|_{L^2}^2 = \underbrace{\frac{1}{2\pi} \int_{r \leq L} |(\mathcal{F}f - W_L \cdot \mathcal{F}f)(x, y)|^2 d(x, y)}_{=: l_1} + \underbrace{\frac{1}{2\pi} \int_{r > L} |\mathcal{F}f(x, y)|^2 d(x, y)}_{=: l_2}.$$

As before, the integral  $l_2$  can be bounded above by

$$l_2 = \frac{1}{2\pi} \int_{r(x, y) > L} |\mathcal{F}f(x, y)|^2 d(x, y) \leq L^{-2\alpha} \|f\|_\alpha^2.$$

# Asymptotic $L^2$ -Error Estimate

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and let  $W \in L^\infty(\mathbb{R})$  be  $k$ -times differentiable at the origin,  $k \geq 2$ , with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1.$$

We again start with

$$\|e_L\|_{L^2}^2 = \underbrace{\frac{1}{2\pi} \int_{r \leq L} |(\mathcal{F}f - W_L \cdot \mathcal{F}f)(x, y)|^2 d(x, y)}_{=: l_1} + \underbrace{\frac{1}{2\pi} \int_{r > L} |\mathcal{F}f(x, y)|^2 d(x, y)}_{=: l_2}.$$

As before, the integral  $l_2$  can be bounded above by

$$l_2 = \frac{1}{2\pi} \int_{r(x, y) > L} |\mathcal{F}f(x, y)|^2 d(x, y) \leq L^{-2\alpha} \|f\|_\alpha^2.$$

For the integral  $l_1$ , we have

$$l_1 = \frac{1}{2\pi} \int_{r(x, y) \leq L} \left| 1 - W\left(\frac{r(x, y)}{L}\right) \right|^2 |\mathcal{F}f(x, y)|^2 d(x, y).$$

# Asymptotic $L^2$ -Error Estimate

Using Taylor's theorem and Lebesgue's theorem on dominated convergence, we get

$$I_1 \leq 2 \phi_{\alpha,L,k}^* \left( \frac{W^{(k)}(0)}{k!} \right)^2 \|f\|_\alpha^2 + \phi_{\alpha,L,k}^* o(1) \quad \text{for } L \rightarrow \infty,$$

where

$$\phi_{\alpha,L,k}^* = \max_{S \in [0,1]} \frac{S^{2k}}{(1 + L^2 S^2)^\alpha} = \max_{S \in [0,1]} \phi_{\alpha,L,k}(S).$$

# Asymptotic $L^2$ -Error Estimate

Using Taylor's theorem and Lebesgue's theorem on dominated convergence, we get

$$I_1 \leq 2 \phi_{\alpha,L,k}^* \left( \frac{W^{(k)}(0)}{k!} \right)^2 \|f\|_\alpha^2 + \phi_{\alpha,L,k}^* o(1) \quad \text{for } L \rightarrow \infty,$$

where

$$\phi_{\alpha,L,k}^* = \max_{S \in [0,1]} \frac{S^{2k}}{(1 + L^2 S^2)^\alpha} = \max_{S \in [0,1]} \phi_{\alpha,L,k}(S).$$

The maximum  $\phi_{\alpha,L,k}^*$  of the function  $\phi_{\alpha,L,k}$  on  $[0, 1]$  can be bounded by

$$\phi_{\alpha,L,k}^* \leq \begin{cases} c_{\alpha,k}^2 L^{-2k} & , \alpha > k \wedge L \geq L^* \\ L^{-2\alpha} & , \alpha \leq k \vee (\alpha > k \wedge L < L^*) \end{cases} = \mathcal{O}\left(L^{-2 \min\{k, \alpha\}}\right)$$

with the critical bandwidth  $L^* = \frac{\sqrt{k}}{\sqrt{\alpha-k}}$  for  $\alpha > k$  and the constant

$$c_{\alpha,k} = \left( \frac{k}{\alpha - k} \right)^{k/2} \left( \frac{\alpha - k}{\alpha} \right)^{\alpha/2}.$$

# Asymptotic $L^2$ -Error Estimate

## Theorem (Asymptotic $L^2$ -error estimate)

Let  $f \in L^1(\mathbb{R}^2) \cap H^\alpha(\mathbb{R}^2)$  for some  $\alpha > 0$ ,  $K_L \in L^1(\mathbb{R}^2)$  and  $W \in L^\infty(\mathbb{R})$  be  $k$ -times differentiable at the origin,  $k \geq 2$ , with

$$W(0) = 1, \quad W^{(j)}(0) = 0 \quad \forall 1 \leq j \leq k-1.$$

Then, the  $L^2$ -norm of the FBP reconstruction error  $e_L = f - f_L$  is bounded above by

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \begin{cases} \left( \frac{\sqrt{2}}{k!} c_{\alpha,k} |W^{(k)}(0)| L^{-k} + L^{-\alpha} \right) \|f\|_\alpha + o(L^{-k}) & , \alpha > k \wedge L \geq L^* \\ \left( \frac{\sqrt{2}}{k!} |W^{(k)}(0)| L^{-\alpha} + L^{-\alpha} \right) \|f\|_\alpha + o(L^{-\alpha}) & , \alpha \leq k \vee (\alpha > k \wedge L < L^*) \end{cases}$$






with the critical bandwidth  $L^* = \frac{\sqrt{k}}{\sqrt{\alpha-k}}$  for  $\alpha > k$  and the constant

$$c_{\alpha,k} = \left( \frac{k}{\alpha-k} \right)^{k/2} \left( \frac{\alpha-k}{\alpha} \right)^{\alpha/2}.$$

*Especially, we have*

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \left( c |W^{(k)}(0)| L^{-\min\{k,\alpha\}} + L^{-\alpha} \right) \|f\|_\alpha + o\left(L^{-\min\{k,\alpha\}}\right).$$



-  M. Beckmann, A. Iske: *Error estimates for filtered back projection*. IEEE International Conference Sampling Theory and Applications (SampTA2015), 2015, 553-557.
-  W.R. Madych: *Summability and approximate reconstruction from Radon transform data*. Contemporary Mathematics, Volume 113, American Mathematical Society, Providence, 1990, 189-219.
-  P. Munshi: *Error analysis of tomographic filters. I: theory*. NDT & E International 25(4/5), 1992, 191-194.
-  P. Munshi, R.K.S. Rathore, K.S. Ram, M.S. Kalra: *Error estimates for tomographic inversion*. Inverse Problems 7(3), 1991, 399-408.
-  F. Natterer: *The Mathematics of Computerized Tomography*. Classics in Applied Mathematics 32, SIAM, Philadelphia, 2001.

Thank you for your attention!