

Saturation Rates for Filtered Back Projection

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DER FORSCHUNG | DER LEHRE | DER BILDUNG

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

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

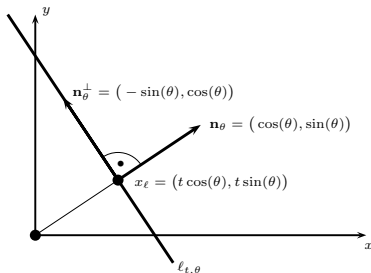
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Analytical solution:

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

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

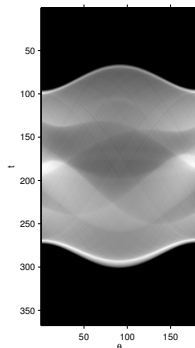
and is given, for $f \in L^1(\mathbb{R}^2) \cap \mathcal{C}(\mathbb{R}^2)$, by the **filtered back projection formula**

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

The Shepp-Logan Phantom and its Radon Transform



The Shepp-Logan phantom f



The Radon transform $\mathcal{R}f$

The Back Projection of the Shepp-Logan Phantom

Original Shepp-Logan Phantom



Unfiltered backprojection



OBS! The filtered back projection formula

$$f(x, y) = \frac{1}{2} \mathcal{B}(\mathcal{F}^{-1}[|S| \mathcal{F}(\mathcal{R}f)(S, \theta)])(x, y)$$

is **ugly** and **unstable**.

OBS! The filtered back projection formula

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is **ugly** and **unstable**.

Stabilization: Replace $|S|$ by a **low-pass filter**

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

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

Approximate Reconstruction

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

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

with *finite bandwidth* $L > 0$ and an *even window function* $W : \mathbb{R} \rightarrow \mathbb{R}$ 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** $K_L : \mathbb{R}^2 \rightarrow \mathbb{R}$ as

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

Three Popular Examples for Low-Pass Filters

The Ram-Lak filter.

$$A_L(S) = |S| \cdot \Pi_L(S) = \begin{cases} |S| & \text{iff } |S| \leq L; \\ 0 & \text{iff } |S| > L. \end{cases}$$

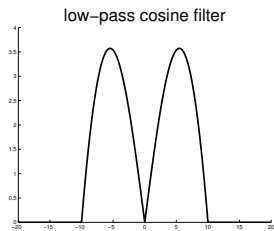
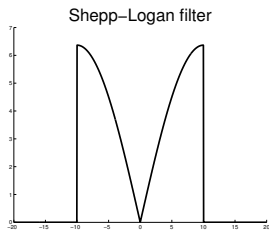
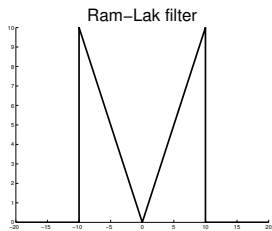
The Shepp-Logan filter.

$$A_L(S) = |S| \cdot \left(\frac{\sin(\pi S/(2L))}{\pi S/(2L)} \right) \cdot \Pi_L(S) = \begin{cases} \frac{2L}{\pi} \cdot |\sin(\pi S/(2L))| & \text{iff } |S| \leq L; \\ 0 & \text{iff } |S| > L. \end{cases}$$

The low-pass cosine filter.

$$A_L(S) = |S| \cdot \cos(\pi S/(2L)) \cdot \Pi_L(S) = \begin{cases} |S| \cdot \cos(\pi S/(2L)) & \text{iff } |S| \leq L; \\ 0 & \text{iff } |S| > L. \end{cases}$$

Three Popular Examples for Low-Pass Filters



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^∞ -error estimates by [Munshi et al., 1991, Munshi, 1992]
- L^p -error estimates in terms of L^p -moduli of continuity by [Madych, 1990]

Our approach:

- L^2 -error estimates for target functions f from Sobolev spaces of fractional order, i.e.,

$$f \in H^\alpha(\mathbb{R}^2) = \{g \in \mathcal{S}'(\mathbb{R}^2) \mid \|g\|_\alpha < \infty\} \quad \text{for } \alpha > 0,$$

where

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

- L^2 -convergence rates ($L \rightarrow \infty$) in terms of bandwidth L and smoothness α

A first L^2 Error Estimate

Theorem (A first L^2 -error estimate; Beckmann & I., 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

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

Proof: For $f \in L^1(\mathbb{R}^2) \cap L^2(\mathbb{R}^2)$ and by the Rayleigh–Plancherel theorem, we get

$$\begin{aligned} \|e_L\|_{L^2(\mathbb{R}^2)}^2 &= \|f - f * K_L\|_{L^2(\mathbb{R}^2)}^2 = \frac{1}{2\pi} \|\mathcal{F}f - \mathcal{F}f \cdot \mathcal{F}K_L\|_{L^2(\mathbb{R}^2; \mathbb{C})}^2 \\ &= \frac{1}{2\pi} \|\mathcal{F}f - W_L \cdot \mathcal{F}f\|_{L^2(\mathbb{R}^2; \mathbb{C})}^2 = I_1 + I_2, \end{aligned}$$

where we used $W_L(\|(x, y)\|_2) = \mathcal{F}K_L(x, y)$ for $K_L \in L^1(\mathbb{R}^2)$, and where we let

$$\begin{aligned} I_1 &:= \frac{1}{2\pi} \int_{\|(x,y)\|_2 \leq L} |(\mathcal{F}f - W_L \cdot \mathcal{F}f)(x, y)|^2 d(x, y), \\ I_2 &:= \frac{1}{2\pi} \int_{\|(x,y)\|_2 > L} |\mathcal{F}f(x, y)|^2 d(x, y). \end{aligned}$$

A first L^2 Error Estimate

Proof (continued):

- For $W \in L^\infty(\mathbb{R})$, the first integral

$$I_1 = \frac{1}{2\pi} \int_{\|(x,y)\|_2 \leq L} |(\mathcal{F}f - W_L \cdot \mathcal{F}f)(x,y)|^2 d(x,y),$$

can be bounded above by

$$I_1 \leq \frac{1}{2\pi} \|1 - W_L\|_{\infty, [-L, L]}^2 \|\mathcal{F}f\|_{L^2(\mathbb{R}^2; \mathbb{C})}^2 = \|1 - W\|_{\infty, [-1, 1]}^2 \|f\|_{L^2(\mathbb{R}^2)}^2.$$

- For $f \in H^\alpha(\mathbb{R}^2)$, with $\alpha > 0$, the second integral

$$I_2 = \frac{1}{2\pi} \int_{\|(x,y)\|_2 > L} |\mathcal{F}f(x,y)|^2 d(x,y)$$

can be bounded above by

$$I_2 \leq \frac{1}{2\pi} \int_{\|(x,y)\|_2 > L} (1 + x^2 + y^2)^\alpha L^{-2\alpha} |\mathcal{F}f(x,y)|^2 d(x,y) \leq L^{-2\alpha} \|f\|_\alpha^2.$$



Refined L^2 -Error Analysis

Theorem (Refined L^2 -error estimate; Beckmann & I., 2016)

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

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

Proof: For $f \in H^\alpha(\mathbb{R}^2)$, with $\alpha > 0$, we bound integral I_2 as before and I_1 by

$$\begin{aligned} I_1 &= \frac{1}{2\pi} \int_{\|(x,y)\|_2 \leq L} \frac{|1 - W_L(\|(x,y)\|_2)|^2}{(1 + x^2 + y^2)^\alpha} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 d(x,y) \\ &\leq \left(\sup_{S \in [-L, L]} \frac{(1 - W_L(S))^2}{(1 + S^2)^\alpha} \right) \frac{1}{2\pi} \int_{\mathbb{R}} \int_{\mathbb{R}} (1 + x^2 + y^2)^\alpha |\mathcal{F}f(x,y)|^2 dx dy. \end{aligned}$$

Refined L^2 -Error Analysis

Proof (continued): Since

$$\sup_{S \in [-L, L]} \frac{(1 - W_L(S))^2}{(1 + S^2)^\alpha} = \sup_{S \in [-L, L]} \frac{(1 - W(S/L))^2}{(1 + S^2)^\alpha} = \sup_{S \in [-1, 1]} \frac{(1 - W(S))^2}{(1 + L^2 S^2)^\alpha},$$

and with letting

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

we find

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

and so

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

□

Refined L^2 -Error Analysis

Theorem (Convergence of $\Phi_{\alpha,W}$; Beckmann & I., 2016)

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

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

Proof (sketch): Let $S_{\alpha,W,L}^* \in [0, 1]$ be the **smallest maximizer** in $[0, 1]$ of

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

Case 1: $S_{\alpha,W,L}^*$ uniformly bounded away from 0, $S_{\alpha,W,L}^* \geq c \equiv c_{\alpha,W} > 0$. Then,

$$0 \leq \Phi_{\alpha,W,L}(S_{\alpha,W,L}^*) = \frac{(1 - W(S_{\alpha,W,L}^*))^2}{(1 + L^2 (S_{\alpha,W,L}^*)^2)^\alpha} \leq \frac{\|1 - W\|_{\infty, [-1,1]}^2}{(1 + L^2 c^2)^\alpha} \xrightarrow{L \rightarrow \infty} 0.$$

Case 2: $S_{\alpha,W,L}^* \longrightarrow 0$ for $L \longrightarrow \infty$. Then,

$$0 \leq \Phi_{\alpha,W,L}(S_{\alpha,W,L}^*) = \frac{(1 - W(S_{\alpha,W,L}^*))^2}{(1 + L^2 (S_{\alpha,W,L}^*)^2)^\alpha} \leq (1 - W(S_{\alpha,W,L}^*))^2 \xrightarrow{L \rightarrow \infty} 0. \quad \square$$

Convergence of the FBP Reconstruction

Corollary (L^2 convergence of FBP reconstruction; Beckmann & I., '16)

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 $W \in C([-1, 1])$ with $W(0) = 1$. Then, the L^2 -norm of the FBP reconstruction error $e_L = f - f_L$ satisfies

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

Basic Assumption

Let $S_{\alpha, W, L}^*$ be uniformly bounded away from 0, i.e., there is $c_{\alpha, W} > 0$ satisfying

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

OBS! Under the basic assumption we have

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

Theorem (Rate of convergence; Beckmann & I., 2016)

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 basic assumption be satisfied for a constant $c_{\alpha, W}$. Then, the L^2 -norm of the FBP reconstruction error $e_L = f - f_L$ is bounded 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,

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

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

OBS! Let the window function $W \in \mathcal{C}([-1, 1])$, $W \not\equiv \chi_{[-1, 1]}$, satisfy

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

for some $0 < \varepsilon < 1$. Then, the basic assumption is fulfilled with $c_{\alpha, W} = \varepsilon$.

Numerical Observations

We investigated the behaviour of $S_{\alpha,W,L}^*$ numerically for standard 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 $\beta > 1$): $W(S) = \exp(-(\pi S/\beta)^2) \cdot \chi_{[-1,1]}(S)$.

- For $\alpha < 2$, we found that the basic assumption

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

is fulfilled whereby

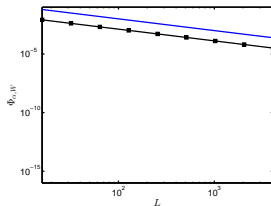
$$\Phi_{\alpha,W}(L) = \mathcal{O}(L^{-2\alpha}) \quad \text{for } L \longrightarrow \infty.$$

- But for $\alpha \geq 2$, we observed $S_{\alpha,W,L}^* \longrightarrow 0$ for $L \longrightarrow \infty$.

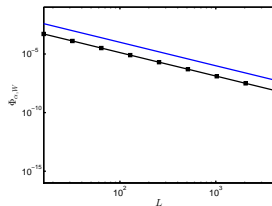
Moreover, in this case the convergence rate of $\Phi_{\alpha,W}$ stagnates at

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

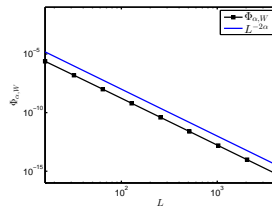
Numerical Observations



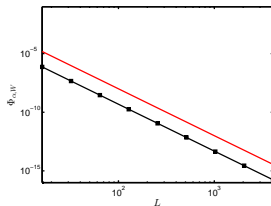
(a) $\alpha = 0.5$



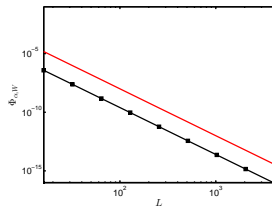
(b) $\alpha = 1$



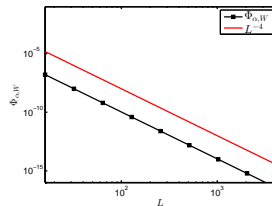
(c) $\alpha = 2$



(d) $\alpha = 2.5$



(e) $\alpha = 3$



(f) $\alpha = 4$

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

L^2 -Error Analysis for C^k -Windows

Theorem (Convergence rate of $\Phi_{\alpha,W}$ for $W \in C^k$; Beckmann & I., '16)

For $k \geq 2$, let $W \in C^k[-1, 1]$ satisfy

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

Then, we have

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

where 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 $\alpha > k$. In particular, we have

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

Corollary (L^2 -error estimate for C^k -windows; Beckmann & I., 2016)

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 $W \in C^k([-1, 1])$, for $k \geq 2$, 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 by

$$\|e_L\|_{L^2(\mathbb{R}^2)} \leq \begin{cases} \left(\frac{c_{\alpha,k}}{k!} \|W^{(k)}\|_{\infty,[-1,1]} L^{-k} + L^{-\alpha} \right) \|f\|_\alpha & \text{for } \alpha > k \\ \left(\frac{1}{k!} \|W^{(k)}\|_{\infty,[-1,1]} L^{-\alpha} + L^{-\alpha} \right) \|f\|_\alpha & \text{for } \alpha \leq k. \end{cases}$$

In particular, we have

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

In conclusion, the rate of convergence saturates at $\mathcal{O}(L^{-k})$. □

Asymptotic L^2 -Error Analysis

Theorem (Asymptotic L^2 -error estimate; Beckmann & I., 2016)

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

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

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

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








with the strictly monotonically decreasing constant

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

In particular, we have

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

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