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A NOTE ON A FIXED POINT METHOD FOR DECONVOLUTION

C. DUVAL¹

ABSTRACT. In this paper we study a particular multidimensional deconvolution problem. The distribution of the noise is assumed to be of the form $G(dx) = (1 - \alpha)\delta(dx) + \alpha g(x)dx$, where δ is the Dirac mass at $0 \in \mathbb{R}^d$, $g : \mathbb{R}^d \rightarrow [0, \infty)$ is a density and $\alpha \in [0, \frac{1}{2}[$. We propose a new estimation procedure, which is not based on a Fourier approach, but on a fixed point method. The performances of the procedure are studied over isotropic Besov balls for L_p loss functions, $1 \leq p < \infty$. A numerical study illustrates the method.

Keywords. Density deconvolution. Nonparametric estimation. Wavelets.

AMS Classification. 62G07, 62H12, 62G20.

1. INTRODUCTION

1.1. **Statistical setting.** Suppose we observe the following multivariate deconvolution model

$$(1) \quad Y_i = X_i + \varepsilon_i, \quad i = 1, \dots, n$$

where (X_i) are i.i.d. (independent and identically distributed) random variables on \mathbb{R}^d , $d \geq 1$, with density $f : \mathbb{R}^d \rightarrow [0, \infty)$ with respect to the Lebesgue measure and independent of (ε_i) which are d dimensional i.i.d. random variables with known distribution G . We aim at estimating f by a fixed point method from the indirect observations (Y_j) and under the following assumption (H1). Suppose there exist a positive number $0 \leq \alpha < 1/2$ and a density function $g : \mathbb{R}^d \rightarrow [0, \infty)$, with respect to the Lebesgue measure, such that

$$(H1) \quad G(dx) = (1 - \alpha)\delta(dx) + \alpha g(x)dx$$

where δ is the Dirac mass concentrated at 0 and $dx = dx_1 \dots dx_d$.

The law of the observations (Y_i) is $f \star G$, where \star denotes the convolution product. Then, to estimate f from the indirect observations (Y_i) , one needs to compute \mathbf{P}^{-1} , the inverse of the convolution operator:

$$\mathbf{P} : f \longrightarrow \mathbf{P}[f] = f \star G.$$

This model has been extensively studied in the literature assuming the distribution G to be absolutely continuous with respect to the Lebesgue measure (which corresponds to $\alpha = 1$). Optimal rates of convergence and adaptive procedures are well known if $d = 1$ (see *e.g.* Carroll and Hall [5], Stefanski [27], Stefanski and Carroll [28], Fan [15], Butucea [1], Butucea and Tsybakov [3, 4], Pensky and Vidakovic [25] or Comte *et al.* [2] for L_2 loss functions or Lounici and Nickl [22] for the L_∞ loss). Results have also been established for multivariate anisotropic densities (see *e.g.* Comte and Lacour [9] for L_2 loss functions or Rebelles [26] for L_p loss functions, $p \in [1, \infty]$). Deconvolution with unknown error distribution has also been studied (see *e.g.* Neumann [24], Delaigle *et al.* [10], Johannes [17] or Meister [23], if an additional error sample is available, or Comte and Lacour [8], Delattre *et al.* [11], Johannes and Schwarz [18], Comte and Kappus [7] or Kappus and Mabon [19] under other set of assumptions).

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The spirit of all the afore-mentioned procedures is to transport the problem in the Fourier domain where the convolution product becomes a simple product, that can be easily inverted. Let $\mathcal{F}[G]$ denote the Fourier transform of a distribution G , dominated by a measure ν , *i.e.*

$$\mathcal{F}[G](u) := \int e^{iuy} G(y) \nu(dy).$$

In the one dimensional setting we have

$$(2) \quad \mathcal{F}[f](u) = \frac{\mathcal{F}[f \star G](u)}{\mathcal{F}[G](u)} \quad \forall u \in \mathbb{R} \text{ such that } \mathcal{F}[G](u) \neq 0.$$

If the distribution G of the noise ε is absolutely continuous with respect to the Lebesgue measure, its Fourier transform is vanishing at infinity. Then, at the points where $\mathcal{F}[G](u)$ gets small, $\mathcal{F}[f](u)$ is badly recovered. It leads to specific minimax rates of convergence, slower than usual nonparametric rates, that depend on how fast $\mathcal{F}[G]$ goes to 0 at infinity (see *e.g.* Fan [15]). A strategy based on (2) leads to an estimator of $\mathcal{F}[f]$, which needs to be sent back in the space of density functions to get an estimator of f . Working with a L_2 loss function together with the use of Plancherel equality facilitate the study of the estimator. This methodology may also be adapted to general L_p loss functions (see *e.g.* Rebelles [26]) using a kernel density estimator with a suitably chosen kernel that takes advantage of the structure of the problem in the Fourier domain.

Recently, Lepski and Willer [21] considered the same convolution model where the distribution of the noise is of the form (H1). For $\alpha \in [0, 1]$, they establish lower bounds for L_p loss functions, $p \in [1, \infty]$, over very general anisotropic Nikol'skii classes. In their paper, if an outline on how to estimate f is suggested, no estimator is given. Therefore the upper bounds are not established. In this paper, we study a methodology based on a fixed point method, that permits to non parametrically estimate the density f for L_p loss functions, $1 \leq p < \infty$ over isotropic Besov balls. For the fixed point procedure to work, we add some restrictions on the distribution of the noise G , namely $\alpha \in [0, \frac{1}{2}[$. The interest of the procedure is threefold. Firstly, we solve a particular deconvolution problem without relying on the specificity of the convolution product in the Fourier domain. Secondly, we provide a consistent estimator of the density f , that is easy to implement numerically. Thirdly, it matches the lower bounds of Lepski and Willer [21] under some additional constraints on α .

1.2. Estimation strategy. We have i.i.d. observations with distribution

$$f \star G(x) = \int_{\mathbb{R}^d} f(y) G(x - y) \nu(dy),$$

where $\nu(dy) = \delta(dy) + dy$ is a dominating measure. Formally, we introduce the convoluting operator \mathbf{P}

$$(3) \quad \begin{aligned} \mathbf{P} : \mathcal{G}(\mathbb{R}^d) &\longrightarrow \mathcal{G}(\mathbb{R}^d) \\ f &\longrightarrow \mathbf{P}[f] := f \star G = G \star f \end{aligned}$$

where $\mathcal{G}(\mathbb{R}^d)$ denotes the set of densities that are absolutely continuous with respect to the Lebesgue measure on \mathbb{R}^d . If we knew analytically the inverse \mathbf{P}^{-1} of \mathbf{P} , such that $\mathbf{P}^{-1}[\mathbf{P}] = \mathbf{I}$, an estimator of f would be naturally

$$\widehat{f} = \mathbf{P}^{-1}[\widehat{\mathbf{P}[f]}]$$

where $\widehat{\mathbf{P}[f]}$ denotes any estimator of $f \star G$ build from the direct observations (Y_1, \dots, Y_n) . Even if we know that \mathbf{P}^{-1} exists, we do not have its analytic form. Here, we do not compute the

inverse \mathbf{P}^{-1} , but we approximate it by a fixed point method. Consider the mapping \mathbf{T} (see also Duval [14])

$$(4) \quad \mathbf{T}[h] = \mathbf{P}[f] + h - \mathbf{P}[h], \quad h \in \mathcal{G}(\mathbb{R}^d).$$

We immediately check that f is a fixed point of \mathbf{T} . If moreover \mathbf{T} is contractant and f belongs to a given Banach space equipped with some norm $\|\cdot\|_B$, applying the Banach fixed point theorem we get $\lim_{K \rightarrow \infty} \|f - \mathbf{T}^{\circ K}[h]\|_B = 0$, for any density h and where \circ denotes the composition product and $\mathbf{T}^{\circ K} = \mathbf{T} \circ \dots \circ \mathbf{T}$, K times. Then, a natural estimator of f is given by

$$\widehat{f}_K = \mathbf{T}^{\circ K}[\widehat{\mathbf{P}}[f]]$$

for a suitable choice of the integer $K \geq 1$.

Predictably enough, to make \mathbf{T} contractant, we need to impose some conditions on G , that is why Assumption (H1) is introduced, with $\alpha \in [0, \frac{1}{2}]$. In that setting, the lower bounds of Lepski and Willer [21] suggests that there exists an estimator converging at usual nonparametric rate. In comparison with the deconvolution models usually studied in the literature ($\alpha = 1$), introducing a Dirac mass in the distribution of the noise G simplifies the estimation problem. Indeed, for $u \in \mathbb{R}$,

$$\mathcal{F}[G](u) = (1 - \alpha) + \alpha \mathcal{F}[g](u)$$

that no longer tends to 0 as $|u| \rightarrow \infty$. This suggests that this specific inverse problem is well-posed and that standard deconvolution procedures based on a Fourier approach should attain usual nonparametric rates of convergence. The introduction of a distribution G with a mass at 0 appears naturally. Indeed, the Dirac mass δ is the neutral element for the convolution product. This is not enough to make \mathbf{T} contractant, we work in a more constrained setting that is $0 < \alpha < \frac{1}{2}$ (see Proposition 1 hereafter). It means that the data set contains at least 50% of direct observations.

We investigate the nonparametric estimation of the density f on any compact set D of \mathbb{R}^d , under Assumption (H1) with $\alpha < 1/2$. We use wavelet threshold density estimators and study their rate of convergence uniformly over isotropic Besov balls for the following L_p loss function, $1 \leq p < \infty$,

$$(5) \quad (\mathbb{E}[\|\widehat{f} - f\|_{L_p(D)}^p])^{1/p},$$

where \widehat{f} is an estimator of f and $\|\cdot\|_{L_p(D)}$ denotes L_p loss over the compact set D . In the sequel we distinguish the norm $\|\cdot\|_{L_p(\mathbb{R}^d)}$ from $\|\cdot\|_{L_p(\nu)}$ as follows

$$\|f\|_{L_p(\mathbb{R}^d)} = \left(\int_{\mathbb{R}^d} |f(x)|^p dx \right)^{1/p} \quad \text{and} \quad \|G\|_{L_p(\nu)} = \left(\int_{\mathbb{R}^d} |G(x)|^p \nu(dx) \right)^{1/p}.$$

1.3. Link with the estimation of random sums. Assumption (H1) can be understood as follows. If $\alpha = 0$, it means that $Y_i = X_i$ for all $i \in \{1, \dots, n\}$ and $\mathbf{P} = \mathbf{I} = \mathbf{P}^{-1}$. On the contrary, $\alpha = 1$ corresponds to the classical deconvolution model (see references above). Finally, $1 > \alpha > 0$ means that α percents of the dataset are blurred observations of X and the others are direct measurements, which is the case when observations are recorded with a device that is sometimes subject to measurement errors. However, we do not know from the dataset (Y_1, \dots, Y_n) which observation is blurred and which is not.

This assumption appears naturally when one estimates the jump density of a jump process, *e.g.* a compound Poisson process or a renewal reward process, from high frequency observations. It can be formalized as a deconvolution problem. Let Z be a jump process with stationary

increments defined by

$$Z_t = \sum_{i=1}^{N_t} \xi_i$$

where N is a counting process with stationary increments and independent of (ξ_i) which are i.i.d. with density f . Without loss of generality one can suppose we observe n nonzero increments of Z at the sampling rate Δ . The distribution of $Z_\Delta | Z_\Delta \neq 0$ is

$$\begin{aligned} & \mathbb{P}(N_\Delta = 1 | N_\Delta \neq 0) f + \sum_{k=2}^{\infty} \mathbb{P}(N_\Delta = k | N_\Delta \neq 0) f^{*k} \\ &= f \star \left(\mathbb{P}(N_\Delta = 1 | N_\Delta \neq 0) \delta + \sum_{k=2}^{\infty} f^{*k-1} \mathbb{P}(N_\Delta = k | N_\Delta \neq 0) \right). \end{aligned}$$

We recover a similar setting as the one studied above. Note that the exact form of \mathbf{P} defined in (3) is unknown since it depends on the counting process N and on the density f itself. A fixed point approach has been investigated in Duval [14] (see also Duval [13] for an explicit computation of \mathbf{P}^{-1}) in the particular case where the process is observed at high frequency, *i.e.* $\Delta \rightarrow 0$. Then, it is possible to estimate f at usual nonparametric rates. The constraint on the sampling rate Δ entails that nonzero increments $(Z_{i\Delta} - Z_{(i-1)\Delta} | Z_{i\Delta} - Z_{(i-1)\Delta} \neq 0)$ are *most of the time* realizations of f , indeed, if Δ is small, we have $\mathbb{P}(N_\Delta = 1 | N_\Delta \neq 0) \approx 1 - \Delta$. We recover a condition similar to Assumption (H1).

2. ESTIMATION OF f

2.1. Preliminary on Besov spaces and wavelet thresholding. In the sequel we consider wavelet threshold density estimators and study their performance uniformly over isotropic Besov balls. In this paragraph we reproduce some classical results on Besov spaces, wavelet bases, wavelet-tensor products and wavelet threshold estimators (see Cohen [6], Donoho *et al.* [12] or Kerkycharian and Picard [20]) that we use in the next sections.

Wavelets and Besov spaces. Let $(\psi_\lambda)_\lambda$ be a regular wavelet basis adapted to the compact set $D \subset \mathbb{R}^d$ (for a precise definition of $(\psi_\lambda)_\lambda$ see hereafter). The multi-index λ concatenates the spatial index and the resolution level $j = |\lambda|$. Set $\Lambda_j := \{\lambda, |\lambda| = j\}$ and $\Lambda = \cup_{j \geq -1} \Lambda_j$, for $f : \mathbb{R}^d \rightarrow [0, \infty)$ in $L_p(\mathbb{R}^d)$ we have

$$(6) \quad f = \sum_{j \geq -1} \sum_{\lambda \in \Lambda_j} \langle f, \psi_\lambda \rangle \psi_\lambda,$$

where $j = -1$ incorporates the low frequency part of the decomposition and $\langle \cdot, \cdot \rangle$ denotes the usual L_2 inner product. Let $s > 0$ and $\pi \in (0, \infty]$, a function f belongs to the Besov space $\mathcal{B}_{\pi\infty}^s(D)$ if the norm

$$(7) \quad \|f\|_{\mathcal{B}_{\pi\infty}^s(D)} := \|f\|_{L_\pi(D)} + \|f^{(\lfloor s \rfloor)}\|_{L_\pi(D)} + \left\| \frac{w_\pi^2(f^{(\lfloor s \rfloor)}, t)}{t^a} \right\|_{L_\infty(D)}$$

is finite, where $s = \lfloor s \rfloor + a$, $\lfloor s \rfloor \in \mathbb{N}$ and $a \in (0, 1]$, w is the modulus of continuity defined by

$$w_\pi^2(f, t) = \sup_{|h| \leq t} \|\mathbf{D}^h \mathbf{D}^h[f]\|_{L_\pi(D)}$$

and $\mathbf{D}^h[f](x) = f(x-h) - f(x)$. Equivalently we can define Besov space in term of wavelet coefficients (see Härdle *et al.* [16] or Kerkycharian and Picard [20]), f belongs to $\mathcal{B}_{\pi\infty}^s(D)$ if

$$\sup_{j \geq -1} 2^{j(s+d(1/2-1/\pi))} \left(\sum_{\lambda \in \Lambda_j} |\langle f, \psi_\lambda \rangle|^\pi \right)^{1/\pi} < \infty,$$

with usual modifications if $\pi = \infty$. We need additional properties on the wavelet basis $(\psi_\lambda)_\lambda$, which are listed in the following assumption.

Assumption 1. *Let $p \geq 1$, it holds that*

- For some $C \geq 1$,

$$C^{-1}2^{d|\lambda|(p/2-1)} \leq \|\psi_\lambda\|_{L_p(D)}^p \leq C2^{d|\lambda|(p/2-1)}.$$

- For some $C > 0$, $\sigma > 0$ and for all $s \leq \sigma$, $J \geq 0$,

$$(8) \quad \left\| f - \sum_{j \leq J} \sum_{\lambda \in \Lambda_j} \langle f, \psi_\lambda \rangle \psi_\lambda \right\|_{L_p(D)} \leq C2^{-Js} \|f\|_{\mathcal{B}_{\pi}^s(D)}.$$

- If $p \geq 1$, for some $C \geq 1$ and for any sequence of coefficients $(u_\lambda)_{\lambda \in \Lambda}$,

$$(9) \quad C^{-1} \left\| \sum_{\lambda \in \Lambda} u_\lambda \psi_\lambda \right\|_{L_p(D)} \leq \left\| \left(\sum_{\lambda \in \Lambda} |u_\lambda \psi_\lambda|^2 \right)^{1/2} \right\|_{L_p(D)} \leq C \left\| \sum_{\lambda \in \Lambda} u_\lambda \psi_\lambda \right\|_{L_p(D)}.$$

- For any subset $\Lambda_0 \subset \Lambda$ and for some $C \geq 1$

$$(10) \quad C^{-1} \sum_{\lambda \in \Lambda_0} \|\psi_\lambda\|_{L_p(D)}^p \leq \int_D \left(\sum_{\lambda \in \Lambda_0} |\psi_\lambda(x)|^2 \right)^{p/2} \leq C \sum_{\lambda \in \Lambda_0} \|\psi_\lambda\|_{L_p(D)}^p.$$

Property (8) ensures that definition (7) of Besov spaces matches the definition in terms of linear approximation. Property (9) ensures that $(\psi_\lambda)_\lambda$ is an unconditional basis of L_p and (10) is a super-concentration inequality (see Kerkycharian and Picard [20] p.304 and p.306).

Wavelet threshold estimator. Let (φ, ψ) be a pair of scaling function and mother wavelet that generate a basis $(\psi_\lambda)_\lambda$. Denote $\varphi_{0\mathbf{k}}(\cdot) = \varphi(\cdot - \mathbf{k})$, $\psi_{j\mathbf{k}}(\cdot) = 2^{j/2}\psi(2^j \cdot - \mathbf{k})$, the associated translated-dilated functions. Consider the triples (j, \mathbf{k}, A) , where $j \in \mathbb{N}$, $\mathbf{k} = (k_1, \dots, k_d) \in \mathbb{Z}^d$ and $A \in S_d$ the set of all non empty subsets of $\{1, \dots, d\}$. Let the functions $\varphi^{\mathbf{k}} : \mathbb{R}^d \rightarrow \mathbb{R}$ and $\psi_{(j, \mathbf{k}, A)} : \mathbb{R}^d \rightarrow \mathbb{R}$ defined by

$$\begin{aligned} \varphi^{\mathbf{k}}(x) &= \varphi^{\mathbf{k}}(x_1, \dots, x_d) = \prod_{i=1}^d \varphi_{0k_i}(x_i), \\ \psi_{(j, \mathbf{k}, A)}(x) &= \psi_{(j, \mathbf{k}, A)}(x_1, \dots, x_d) = \prod_{i \in A} \psi_{jk_i}(x_i) \prod_{i \in A^c} \varphi_{jk_i}(x_i). \end{aligned}$$

The system $\{\varphi^{\mathbf{k}}, \mathbf{k} \in \mathbb{Z}^d, \psi_{(j, \mathbf{k}, A)}, j \in \mathbb{N}, \mathbf{k} \in \mathbb{Z}^d, A \in S_d\}$ is a wavelet-tensor product. If constructed on compactly supported wavelets (φ, ψ) , it satisfies Assumption 1 for some $\sigma > 0$ (see Kerkycharian and Picard [20] pp. 305, 306 and 314-315). To simplify notation, we write the basis $\{\psi_{jk}, j \in \mathbb{N}, k \in A_j\}$ where A_j is a set of cardinality proportional to 2^{jd} and incorporates boundary terms that we choose not to distinguish in the notation. Then, (6) becomes

$$f = \sum_{j \geq 0} \sum_{k \in A_j} \gamma_{jk} \psi_{jk},$$

where $\gamma_{jk} = \int_{\mathbb{R}^d} \psi_{jk}(x) f(x) dx$. We consider classical hard threshold estimators of the form

$$\widehat{f}(\cdot) = \sum_{j=0}^J \sum_{k \in A_j} \widehat{\gamma}_{jk} \mathbb{1}_{\{|\widehat{\gamma}_{jk}| \geq \eta\}} \psi_{jk}(\cdot),$$

where $\widehat{\gamma}_{jk}$ is an estimator of γ_{jk} , J and η are respectively the resolution level and the threshold, possibly depending on the data.

2.2. Construction of the estimator. We estimate densities f which satisfy a smoothness property in term of Besov balls

$$(11) \quad \mathcal{G}(s, \pi, M) = \{f \in \mathcal{G}(\mathbb{R}), \|f\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \leq M\},$$

where M is a positive constant. The fact that f is in a Besov space $\mathcal{B}_{\pi,\infty}^s(\mathbb{R}^d)$ is used to approximate \mathbf{P}^{-1} with a fixed point method. The fact that its Besov norm is bounded is used to control the risk of the estimator over the ball $\mathcal{G}(s, \pi, M)$.

Construction of the inverse. For $\pi \geq 1$, the space $\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$ is a Banach space if equipped with the Besov norm (7). Consider the mapping \mathbf{T} , for which f is a fixed point, defined for h in $\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$ by

$$(12) \quad \mathbf{T}[h] := \mathbf{P}[f] + h - \mathbf{P}[h],$$

where \mathbf{P} is defined in (3). The following Proposition 1 guarantees that the definition of the operator (12) matches the assumptions of the Banach fixed point theorem.

Proposition 1. *Let $\pi \geq 1$ and $0 < \alpha < \frac{1}{2}$. Then, the mapping \mathbf{T} sends elements of $\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$ into itself and is a contraction. For all $h_1, h_2 \in \mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$ we have*

$$\|\mathbf{T}[h_1] - \mathbf{T}[h_2]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \leq 2\alpha \|h_1 - h_2\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)}.$$

Proposition 1 permits to apply the Banach fixed point theorem: let $0 < \alpha < \frac{1}{2}$, we derive that f is the unique fixed point of \mathbf{T} and from any initial point h_0 in $\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$ we have

$$\|f - \mathbf{T}^{\circ K}[h_0]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \longrightarrow 0 \quad \text{as } K \rightarrow \infty.$$

We choose $h_0 = \mathbf{P}[f]$ as initial point as we can construct an optimal estimator of $\mathbf{P}[f]$ from the observations (Y_1, \dots, Y_n) (Lemma 1 in Section 4 ensures that $\mathbf{P}[f]$ is in $\mathcal{G}(s, \pi, M) \subset \mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$).

Remark 1. *The restriction on α is imposed by the factor 2 in the contraction property. This factor seems unavoidable: we control the difference of 2 singular probability measures, one absolutely continuous with respect to the Lebesgue measure and the other with the Dirac mass δ . This factor 2 seems sharp and the operator \mathbf{T} might be useless to approximate \mathbf{P}^{-1} for $\alpha \geq \frac{1}{2}$.*

Proposition 2. *Let $K \geq 0$, it holds that*

$$\mathbf{T}^{\circ K}[\mathbf{P}[f]] = \mathbf{H}_K[G] \star \mathbf{P}[f]$$

where for $K \geq 1$, \mathbf{H}_K is given by $\mathbf{H}_K[G] = \sum_{k=1}^{K+1} C_{K+1}^k (-1)^{k+1} G^{\star k}$ and we set $\mathbf{H}_0[G] = \delta$.

Note that $G \star \mathbf{H}_K[G] = \delta - (\delta - G)^{\star K+1}$. Proposition 2 is useful from a numerical point of view. It permits to easily compute $\mathbf{T}^{\circ K}[\mathbf{P}[f]]$, where replacing $\mathbf{P}[f]$ by an estimator leads to our estimator.

Construction of an estimator of $\mathbf{P}[f]$. Define the wavelet coefficients

$$(13) \quad \widehat{\gamma}_{jk} = \frac{1}{n} \sum_{i=1}^n \psi_{jk}(Y_i).$$

Let $\eta > 0$ and $J \in \mathbb{N} \setminus \{0\}$, define \widehat{P} the estimator of $\mathbf{P}[f]$ over D as

$$(14) \quad \widehat{P}(x) = \sum_{j=0}^J \sum_{k \in A_j} \widehat{\gamma}_{jk} \mathbf{1}_{\{|\widehat{\gamma}_{jk}| \geq \eta\}} \psi_{jk}(x), \quad x \in D.$$

Definition 1. Let \widehat{f}_K be an estimator of f defined for K in \mathbb{N} and x in D as

$$(15) \quad \widehat{f}_K(x) = \mathbf{H}_K[G] \star \widehat{P}(x)$$

where \mathbf{H}_K is defined in Proposition 2.

The estimator \widehat{f}_K may be interpreted as follows, if $\alpha = 0$ then $f = \mathbf{P}[f]$, which can be directly estimated, and one should have $K = 0$. However, if $\alpha > 0$, the dataset is contaminated with blurred observations that need to be counterbalanced by the addition of K corrections. For instance, suppose $\alpha = n^{-1/4}$. Straightforward computations lead to

$$T[\mathbf{P}[f]] = (1 - n^{-1/2})f + O(n^{-1/2})$$

whereas the direct approximation is $\mathbf{P}[f] = (1 - n^{-1/4})f + O(n^{-1/4})$. Then, applying \mathbf{T} permits to approximate f more rapidly than the crude approximation of $\mathbf{P}[f]$.

2.3. Convergence rates and discussion.

Theorem 1. We work under Assumption 1. Let $p \geq \pi \geq 1$, $\sigma > s > 1/\pi$ and \widehat{P} be the threshold wavelet estimator of $\mathbf{P}[f]$ on D defined in (14). Take J such that $2^{Jd}n^{-1} \log(n^{1/2}) \leq 1$ and $\eta = \kappa n^{-1/2} \sqrt{\log(n^{1/2})}$, for some $\kappa > 0$.

- (1) The estimator \widehat{P} of $\mathbf{P}[f]$ satisfies for sufficiently large $\kappa > 0$

$$\sup_{\mathbf{P}[f] \in \mathcal{G}(s, \pi, M)} (\mathbb{E}[\|\widehat{P} - \mathbf{P}[f]\|_{L_p(D)}^p])^{1/p} \leq C n^{-\delta(s, p, \pi)},$$

up to logarithmic factors in n , where

$$(16) \quad \delta(s, p, \pi) = \min \left\{ \frac{s}{2s + d}, \frac{s + d/p - d/\pi}{2(s + d/2 - d/\pi)} \right\}$$

and C depends on s, π, p, M, ψ . An explicit bound for κ is given in Lemma 3.

- (2) Suppose moreover that Assumption (H1) holds. The estimator \widehat{f}_K for $K \in \mathbb{N}$ defined in (15) satisfies for sufficiently large $\kappa > 0$

$$\sup_{f \in \mathcal{G}(s, \pi, M)} (\mathbb{E}[\|\widehat{f}_K - f\|_{L_p(D)}^p])^{1/p} \leq \max \left(2^K n^{-\delta(s, p, \pi)}, (2\alpha)^{K+1} M \right),$$

up to logarithmic factors in n , where C depends on s, π, p, M, ψ .

Proof of Theorem 1 is postponed to Section 4. Note that the estimator \widehat{f}_K with J and η chosen as in Theorem 1 is adaptive, recall that K is chosen by the practitioner. This upper bound is easy to interpret. The estimator cannot perform well if \mathbf{P}^{-1} is poorly approximated by $\mathbf{T}^{\circ K}$, it leads to the deterministic loss $(2\alpha)^{K+1}$. It also cannot perform better than the estimator \widehat{P} of $\mathbf{P}[f]$, which imposes the random error $n^{-\delta(s, p, \pi)}$, this is optimal. However, there is an additional constant in 2^K , that may not be negligible. It is due to the form of the estimator that may be rewritten:

$$\widehat{f}_K(x) = \sum_{k=1}^{K+1} C_{K+1}^k (-1)^{k+1} G^{*k} \star \widehat{P}(x).$$

Ideally, we should take K such that the deterministic error is negligible compared to the random error and would realize the tradeoff $2^K n^{-\delta(s, p, \pi)} \asymp (2\alpha)^{K+1}$. As $\delta(s, p, \pi)$ is unknown, we use that $\delta(s, p, \pi) \leq \frac{1}{2}$, which leads to the adaptive choice K^* , the smallest integer such that $n^{-\frac{1}{2}} > 2\alpha^{K+1}$

$$(17) \quad K^* \asymp \left\lceil \frac{1}{2} \frac{\log(n)}{\log(\frac{1}{\alpha})} - 1 \right\rceil.$$

We have $K^* := K^*(\alpha)$ that is increasing with α .

However, this choice of K^* , if it gives a consistent procedure, may not attain minimax rates of convergence. Indeed, the resulting rate is $2^{K^*} n^{-\delta(s,p,\pi)}$ (up to logarithmic terms in n). If K^* gets too large, 2^{K^*} deteriorates the rate of convergence. The question may be reformulated as follows, how large can α be for the procedure to be rate optimal *i.e.* such that 2^{K^*} entails at most a logarithmic loss in n . If $K = O(\log(\log(n)))$ then α_n^* the maximum α for which the procedure attains the minimax rate is

$$\alpha_n^* = \exp\left(-\frac{\log(n)}{2\log(\log(n))}\right).$$

Note that $\alpha_n^* \rightarrow 0$ as $n \rightarrow \infty$. But, in the cases where $\alpha := \alpha_n \leq \alpha_n^*$, \hat{f}_{K^*} is rate optimal and converges at usual nonparametric rate, up to a logarithmic loss. It matches the lower bound of Lepski and Willer [21]. Nonetheless, the aim of the present note is not to solve this particular problem, but to stress that it is possible to solve a deconvolution problem without relying on a Fourier argument and underline the fact that fixed point approaches are possible tools to solve inverse problems.

3. NUMERICAL STUDY

In this Section we illustrate, in the univariate setting, how the method performs on simulated data and examine in particular its behavior when K increases and α is varying. We also compare its performances with an oracle: the wavelet estimator we would compute in the idealized framework where direct observations $(X_i, 1 \leq i \leq n)$ are available.

Wavelet estimators are based on the evaluation of the first wavelet coefficients. To perform those we use Symlets 16 wavelet functions, that are compactly supported and satisfy Assumption 1. Moreover we transform the data in an equispaced signal on a grid of length 2^L with $L = 8$. It is the binning procedure (see Härdle *et al.* [16] Chap. 12). The threshold and the resolution level are chosen as in Theorem 1. The parameter κ is taken equal to 1. The estimators we compute take the form of a vector giving the estimated values of the density f on the uniform grid $[a, b]$ with mesh 0.01, where a and b are adapted to the estimated density f . We use the wavelet toolbox of Matlab. To compute \hat{f}_K for $K \geq 1$, we compute $(G^{*k} \star \hat{P}, 1 \leq k \leq K - 1)$ with the function `conv` of Matlab.

Figure 1 represents the estimation procedure for different values of $K \in \{0, 1, 2\}$, $\alpha = 0.25$, g a Gaussian density with mean 3 and variance 0.5 and f being the following mixture:

$$0.2\mathcal{N}(-2, 1) + 0.8\mathcal{N}(2, 1)$$

All the estimators are evaluated on the same trajectory. They all manage to reproduce the shape of the density f but \hat{f}_0 and \hat{f}_1 are biased. Increasing K permits to reduce this bias. Even though the optimal choice for K given by (17) is 4, it seems that with $K = 2$ we already have a good estimation of the mixture.

Evaluation of L_2 risks confirms the former graphical observation. We approximate the L_2 errors by Monte Carlo. For that we compute $M = 1000$ times each estimator, for each iteration, the estimators $(\hat{f}_K)_{K \geq 0}$ are computed on the same dataset $(Y_j, 1 \leq j \leq n)$ and the oracle on the direct observations $(X_i, 1 \leq i \leq n)$ used to compute the values $(Y_j, 1 \leq j \leq n)$. The results are reproduced in Tables 1, 2 and 3.

In Table 2 we observe that the procedure is meaningful, regardless the density g . The L_2 risks decrease with K , until K gets larger than K^* defined in (17), afterwards, they get stable. Also it appears that the most significant gains in the risk come from the first iterations of the fixed point method ($K \in \{1, 2\}$) and that the gain is less important then. In Table 3 we see that even for large values of α the procedure works. In both Tables, even the risks associated to \hat{f}_{K^*} are larger than the oracle ones, even for large values of n . It can be explained by the fact

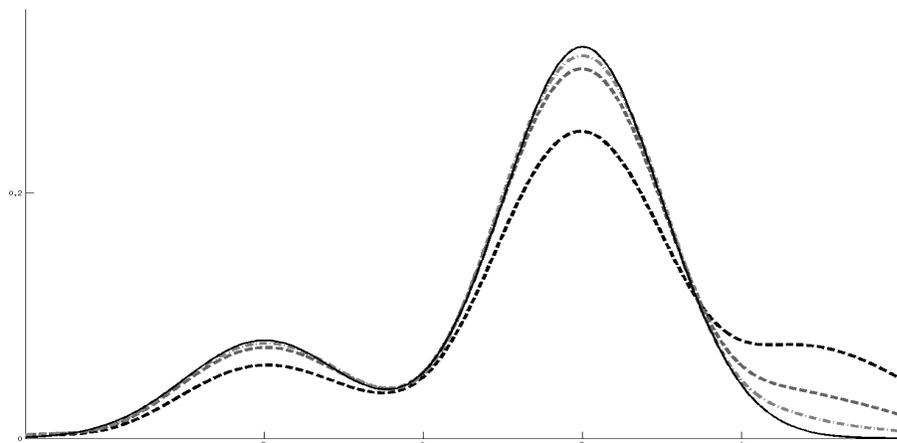


FIGURE 1. Estimators of the density f (plain black) for $n = 10^6$ and $\alpha = 0.25$: \hat{f}_0 (dotted black), \hat{f}_1 (dotted dark grey) and \hat{f}_2 (dashed light grey).

that the minimax rate can be attained only for values of α that are close to 0. Indeed for the values of α and n of Table 3, we have $2^{K^*} \alpha^{K^*+1} = 0.1$ which is the limiting term in the rate according to Theorem 1. If we take α small enough such that the associated K is smaller than $\log(\log(n))$ as in Table 1 where $\alpha = 0.03$, we observe that our procedure attain the oracle rate, that is minimax. Numerical results are consistent with the theoretical results of Theorem 1.

g	n (K^*)	Oracle	\hat{f}_0	\hat{f}_1	\hat{f}_2	\hat{f}_3
$\mathcal{N}(2, 2)$	10^4	0.29×10^{-3}	0.83×10^{-3}	0.66×10^{-3}	0.66×10^{-3}	0.66×10^{-3}
	(1)	(0.20×10^{-3})	(0.35×10^{-3})	(0.31×10^{-3})	(0.31×10^{-3})	(0.31×10^{-3})
$\mathcal{U}([-1, 3])$	10^5	0.07×10^{-3}	0.19×10^{-3}	0.04×10^{-3}	0.04×10^{-3}	0.04×10^{-3}
	(1)	(0.29×10^{-4})	(0.35×10^{-4})	(0.21×10^{-4})	(0.21×10^{-4})	(0.21×10^{-4})
$\mathcal{U}([-1, 3])$	10^4	0.29×10^{-3}	0.30×10^{-3}	0.24×10^{-3}	0.24×10^{-3}	0.24×10^{-3}
	(1)	(0.20×10^{-3})	(0.17×10^{-3})	(0.17×10^{-3})	(0.17×10^{-3})	(0.17×10^{-3})
$\mathcal{U}([-1, 3])$	10^5	0.07×10^{-3}	0.15×10^{-3}	0.09×10^{-3}	0.09×10^{-3}	0.09×10^{-3}
	(1)	(0.28×10^{-4})	(0.44×10^{-4})	(0.41×10^{-4})	(0.41×10^{-4})	(0.41×10^{-4})

TABLE 1. Mean of the L_2 -risks for different values of K and the oracle estimator; standard deviation in parenthesis. In this case, f is $\mathcal{N}(1, 1)$, $\alpha = 0.03$ and $D = [-3, 4]$. In bold it is the loss of the estimator \hat{f}_{K^*} , where K^* is chosen as in (17).

4. PROOFS

In the sequel C denotes a constant which may vary from line to line. Its dependency in other constants are sometimes given in subscripts.

4.1. Preliminary. We establish a technical lemma, which states that regularity assumptions on f transfer to $\mathbf{P}[f]$.

Lemma 1. *If f belongs to $\mathcal{G}(s, \pi, M)$ then, $\mathbf{P}[f]$ also belongs to $\mathcal{G}(s, \pi, M)$.*

g	$n(K^*)$	Oracle	\widehat{f}_0	\widehat{f}_1	\widehat{f}_2	\widehat{f}_3
$\mathcal{N}(2, 2)$	10^4 (1)	0.28×10^{-3} (0.19×10^{-3})	2.62×10^{-3} (0.58×10^{-3})	1.06×10^{-3} (0.44×10^{-3})	1.00×10^{-3} (0.42×10^{-3})	1.00×10^{-3} (0.42×10^{-3})
	10^5 (2)	0.07×10^{-3} (0.03×10^{-3})	1.77×10^{-3} (0.11×10^{-3})	0.32×10^{-3} (0.05×10^{-3})	0.27×10^{-3} (0.05×10^{-3})	0.27×10^{-3} (0.05×10^{-3})
$\mathcal{U}([-1, 3])$	10^4 (1)	0.29×10^{-3} (0.20×10^{-3})	1.09×10^{-3} (0.27×10^{-3})	0.54×10^{-3} (0.24×10^{-3})	0.53×10^{-3} (0.24×10^{-3})	0.53×10^{-3} (0.24×10^{-3})
	10^5 (2)	0.07×10^{-3} (0.28×10^{-4})	0.93×10^{-3} (0.88×10^{-4})	0.40×10^{-3} (0.67×10^{-4})	0.38×10^{-3} (0.67×10^{-4})	0.38×10^{-3} (0.67×10^{-4})
$\mathcal{E}(2)$	10^4 (1)	0.28×10^{-3} (0.19×10^{-3})	1.87×10^{-3} (0.67×10^{-3})	0.97×10^{-3} (0.58×10^{-3})	0.94×10^{-3} (0.57×10^{-3})	0.94×10^{-3} (0.57×10^{-3})
	10^5 (2)	0.07×10^{-3} (0.03×10^{-3})	1.34×10^{-3} (0.15×10^{-3})	0.52×10^{-3} (0.13×10^{-3})	0.49×10^{-3} (0.13×10^{-3})	0.49×10^{-3} (0.13×10^{-3})

TABLE 2. Mean of the L_2 -risks for different values of K and the oracle estimator; standard deviation in parenthesis. In this case, f is $\mathcal{N}(1, 1)$, $\alpha = 0.1$ and $D = [-3, 4]$. In bold it is the loss of the estimator \widehat{f}_{K^*} , where K^* is chosen as in (17).

g	$n(K^*)$	Oracle	\widehat{f}_0	\widehat{f}_1	\widehat{f}_2	\widehat{f}_{K^*}
$\mathcal{N}(2, 2)$	10^5 (6)	0.07×10^{-3} (0.03×10^{-3})	2.78×10^{-2} (0.67×10^{-3})	1.07×10^{-2} (0.60×10^{-3})	0.72×10^{-2} (0.53×10^{-3})	0.61×10^{-2} (0.52×10^{-3})
	10^5 (6)	0.07×10^{-3} (0.28×10^{-4})	1.34×10^{-2} (0.34×10^{-3})	0.76×10^{-2} (0.33×10^{-3})	0.67×10^{-2} (0.32×10^{-3})	0.65×10^{-2} (0.32×10^{-32})

TABLE 3. Mean of the L_2 -risks for different values of K and the oracle estimator; standard deviation in parenthesis. In this case, f is $\mathcal{N}(1, 1)$, $\alpha = 0.4$ and $D = [-3, 4]$. In bold it is the loss of the estimator \widehat{f}_{K^*} , where K^* is chosen as in (17).

Proof of Lemma 1. It is straightforward to derive $\|\mathbf{P}[f]\|_{L_1(\nu)} = 1$. The remainder of the proof is a consequence of the following result: Let $f \in \mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$ and $g \in L_1(\mathbb{R}^d)$ we have

$$(18) \quad \|f \star g\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \leq \|f\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \|g\|_{L_1(\mathbb{R}^d)}.$$

To prove (18) we use the definition of the Besov norm (7); the result is a consequence of Young's inequality and elementary properties of the convolution product. First, Young's inequality gives

$$(19) \quad \|f \star g\|_{L_\pi(\mathbb{R}^d)} \leq \|f\|_{L_\pi(\mathbb{R}^d)} \|g\|_{L_1(\mathbb{R}^d)}.$$

Second, the differentiation property of the convolution product leads for $n \geq 1$ to

$$(20) \quad \left\| \frac{d^n}{dx^n} (f \star g) \right\|_{L_\pi(\mathbb{R}^d)} = \left\| \left(\frac{d^n}{dx^n} f \right) \star g \right\|_{L_\pi(\mathbb{R}^d)} \leq \left\| \frac{d^n}{dx^n} f \right\|_{L_\pi(\mathbb{R}^d)} \|g\|_{L_1(\mathbb{R}^d)}.$$

Finally, translation invariance of the convolution product gives

$$(21) \quad \|\mathbf{D}^h \mathbf{D}^h [(f \star g)^{(n)}]\|_{L_\pi(\mathbb{R}^d)} = \|(\mathbf{D}^h \mathbf{D}^h [f^{(n)}]) \star g\|_{L_\pi(\mathbb{R}^d)} \leq \|\mathbf{D}^h \mathbf{D}^h [f^{(n)}]\|_{L_\pi(\mathbb{R}^d)} \|g\|_{L_1(\mathbb{R}^d)}.$$

Inequality (18) is then obtained by bounding $\|f \star g\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)}$ using (19), (20) and (21). We now complete the proof of Lemma 1, using the triangle inequality and (18)

$$\|\mathbf{P}[f]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} = \|G \star f\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} = \|(1 - \alpha)f + \alpha g \star f\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \leq \|f\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \leq M,$$

where α and g are defined in (H1). The proof is now complete. \square

4.2. Proof of Proposition 1. We show that \mathbf{T} is a contraction that sends elements of $\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$ into $\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$. We have for all $h_1, h_2 \in \mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$

$$\mathbf{T}[h_1] - \mathbf{T}[h_2] = h_1 - h_2 - G \star (h_1 - h_2) = \alpha(h_1 - h_2) - \alpha g \star (h_1 - h_2).$$

It follows from Young's inequality and assumption (H1) that

$$\|\mathbf{T}[h_1] - \mathbf{T}[h_2]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \leq 2\alpha\|h_1 - h_2\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)}.$$

Finally, let $h \in \mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$. The last assertion together with the fact that the null function is in $\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)$ and Lemma 1 lead to

$$\begin{aligned} \|\mathbf{T}[h]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} &\leq \|\mathbf{T}[0]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} + \|\mathbf{T}[h] - \mathbf{T}[0]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \\ &\leq \|\mathbf{P}[f]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} + 2\alpha\|h\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} < \infty. \end{aligned}$$

The proof is now complete.

4.3. Proof of Proposition 2. A proof by induction readily gives the result. It holds for $K = 1$, assuming the result at rank K we have

$$\begin{aligned} \mathbf{T}^{\circ K+1}[\mathbf{P}[f]] &= \mathbf{T}[\mathbf{T}^{\circ K}[\mathbf{P}[f]]] = \mathbf{P}[f] + \mathbf{H}_K[G] \star \mathbf{P}[f] - G \star \mathbf{H}_K[G] \star \mathbf{P}[f] \\ &= (\delta + \mathbf{H}_K[G] - G \star \mathbf{H}_K[G]) \star \mathbf{P}[f]. \end{aligned}$$

$$\begin{aligned} \text{Then, } G \star (\delta + \mathbf{H}_K[G] - G \star \mathbf{H}_K[G]) &= G + G \star \mathbf{H}_K[G] - G \star G \star \mathbf{H}_K[G] \\ &= G + \delta - (\delta - G)^{\star K+1} - G \star (\delta - (\delta - G)^{\star K+1}) \\ &= \delta - (\delta - G) \star (\delta - G)^{\star K+1} = \delta - (\delta - G)^{K+2}, \end{aligned}$$

which concludes the proof.

4.4. Proof of Theorem 1.

Proof of part 1) of Theorem 1. To prove part 1) of Theorem 1 we apply the general results of Kerkyacharian and Picard [20]. For that we state some technical lemmas whose proof is based on classical Rosenthal's and Bernstein's inequalities.

Lemma 2. *Let $2^{jd} \leq n$, then for $p \geq 1$ we have*

$$\mathbb{E}[|\widehat{\gamma}_{jk} - \gamma_{jk}|^p] \leq Cn^{-p/2},$$

where C depends on p , $\|\psi\|_{L_p(\mathbb{R}^d)}$, M and $\widehat{\gamma}_{jk}$ is defined in (13) and

$$(22) \quad \gamma_{jk} = \int_{\mathbb{R}^d} \psi_{jk}(y) \mathbf{P}[f](y) dy.$$

Proof of Lemma 2. The result is obtained applying Rosenthal's inequality: let $p \geq 1$ and let (U_1, \dots, U_n) be centered independent real random variables such that $\mathbb{E}[|U_i|^p] < \infty$. Then there exists C_p such that

$$(23) \quad \mathbb{E}\left[\left|\sum_{i=1}^n U_i\right|^p\right] \leq C_p \left\{ \sum_{i=1}^n \mathbb{E}[|U_i|^p] + \left(\sum_{i=1}^n \mathbb{E}[|U_i|^2]\right)^{p/2} \right\}.$$

Set $Z_i = \psi_{jk}(Y_i)$, for $p \geq 1$ we have by convex inequality

$$\begin{aligned} \mathbb{E}[|Z_i - \mathbb{E}[Z_i]|^p] &\leq 2^p \mathbb{E}[|Z_i|^p] \leq 2^p 2^{jd p/2} \int_{\mathbb{R}^d} |\psi(2^j y - k)|^p \mathbf{P}[f](y) dy \\ &= 2^p 2^{jd(p/2-1)} \int_{\mathbb{R}^d} |\psi(z)|^p \mathbf{P}[f](2^{-j}(z - k)) dy \end{aligned}$$

where we made the substitution $z = 2^j y - k$. Lemma 1 and Sobolev embeddings (see [6, 12, 16])

$$(24) \quad \mathcal{B}_{\pi\infty}^s \hookrightarrow \mathcal{B}_{p\infty}^{s'} \quad \text{and} \quad \mathcal{B}_{\pi\infty}^{s'} \hookrightarrow \mathcal{B}_{\infty\infty}^s,$$

where $p > \pi$, $s\pi > 1$ and $s' = s - 1/\pi + 1/p$, give $\|\mathbf{P}[f]\|_\infty \leq M$. It follows that

$$\mathbb{E}[|Z_i - \mathbb{E}[Z_i]|^p] \leq 2^p 2^{jd(p/2-1)} \|\psi\|_{L_p(\mathbb{R}^d)}^p M$$

and $\mathbb{E}[|Z_i - \mathbb{E}[Z_i]|^2] \leq M$ since $\|\psi\|_{L_2(\mathbb{R}^d)} = 1$. Rosenthal's inequality (23) gives for $p \geq 1$

$$\mathbb{E}[|\hat{\gamma}_{jk} - \gamma_{jk}|^p] \leq C_p \left\{ 2^p \left(\frac{2^{jd}}{n} \right)^{\frac{p}{2}-1} \|\psi\|_{L_p(\mathbb{R}^d)}^p M + M^{p/2} \right\} n^{-\frac{p}{2}}.$$

Finally, since $2^{jd} \leq n$

$$\mathbb{E}[|\hat{\gamma}_{jk} - \gamma_{jk}|^p] \leq C_{p, \|\psi\|_{L_p(\mathbb{R}^d)}, M} n^{-p/2}.$$

This completes the proof. \square

Lemma 3. *Choose j and c such that*

$$2^{jd} n^{-1} \log(n^{1/2}) \leq 1 \quad \text{and} \quad c^2 \geq 8 \left(M + \frac{c \|\psi\|_\infty}{3} \right).$$

For all $r \geq 1$, let $\kappa_r = cr$. We have

$$\mathbb{P}\left(|\hat{\gamma}_{jk} - \gamma_{jk}| \geq \frac{\kappa_r}{2} n^{-1/2} \sqrt{\log(n^{1/2})}\right) \leq n^{-r/2},$$

where $\hat{\gamma}_{jk}$ is defined in (13) and γ_{jk} in (22).

Proof of Lemma 3. The proof is obtained with Bernstein's inequality. Consider U_1, \dots, U_n centered, bounded and independent real random variables such that $|U_i| \leq S$ and set $s_n^2 = \sum_{i=1}^n \mathbb{E}[U_i^2]$. Then for any $\lambda > 0$,

$$(25) \quad \mathbb{P}\left(\left|\sum_{i=1}^n U_i\right| > \lambda\right) \leq 2 \exp\left(-\frac{\lambda^2}{2(s_n^2 + \frac{\lambda S}{3})}\right).$$

We keep notation Z_i introduced in the proof of Lemma 2, $\hat{\gamma}_{jk} - \gamma_{jk}$ is a sum of centered and identically distributed random variables bounded by $2^{jd/2} \|\psi\|_\infty$ such that $\mathbb{E}[|Z_i - \mathbb{E}[Z_i]|^2] \leq M$. It follows from (25)

$$\begin{aligned} \mathbb{P}\left(|\hat{\gamma}_{jk} - \gamma_{jk}| \geq \frac{\kappa_r}{2} n^{-1/2} \sqrt{\log(n^{1/2})}\right) &= \mathbb{P}\left(\left|\sum_{i=1}^n Z_i - \mathbb{E}(Z_i)\right| \geq \frac{\kappa_r}{2} n^{1/2} \sqrt{\log(n^{1/2})}\right) \\ &\leq 2 \exp\left(-\frac{\kappa_r^2 \log(n^{1/2})}{8 \left(M + \frac{\kappa_r 2^{jd/2} n^{-1/2} \sqrt{\log(n^{1/2})} \|\psi\|_\infty}{3}\right)}\right). \end{aligned}$$

Using that $2^{jd} n^{-1} \log(n^{1/2}) \leq 1$ we have

$$\mathbb{P}\left(|\hat{\gamma}_{jk} - \gamma_{jk}| \geq \frac{\kappa_r}{2} n^{-1/2} \sqrt{\log(n^{1/2})}\right) \leq 2 \exp\left(-\frac{c^2 r}{8 \left(M + \frac{\kappa_r \|\psi\|_\infty}{3}\right)} r \log(n^{1/2})\right) \leq n^{-r/2},$$

if $c^2 \geq 8 \left(M + \frac{c \|\psi\|_\infty}{3}\right)$ and $r \geq 1$. The proof is complete. \square

Proof of of part 1) of Theorem 1. It is a consequence of Lemma 1, 2, 3 and of the general theory of wavelet threshold estimators of Kerkyacharian and Picard [20]. Let J , such that $2^{Jd} = n(\log(n))^{-1}$. Conditions (5.1) and (5.2) of Theorem 5.1 of [20], are satisfied –Lemma 2 and 3– with $c(n) = n^{-1/2} \sqrt{\log(n)}$ and $\Lambda_n = c(n)^{-1}$ (with the notation of [20]), we can now apply Theorem 5.1, its Corollary 5.1 and Theorem 6.1 of [20] to obtain the result. \square

Completion of the proof of Theorem 1. We decompose the L_p loss as follows, using notation of Proposition 2 and Definition 1

$$(26) \quad (\mathbb{E}[\|\widehat{f}_K - f\|_{L_p(D)}^p])^{\frac{1}{p}} \leq (\mathbb{E}[\|\widehat{f}_K - \mathbf{H}_K[G] \star \mathbf{P}[f]\|_{L_p(D)}^p])^{\frac{1}{p}} + \|\mathbf{H}_K[G] \star \mathbf{P}[f] - f\|_{L_p(D)}.$$

An upper bound for the first term is given by part 1) of Theorem 1, the triangle inequality and Young's inequality

$$(27) \quad \begin{aligned} \mathbb{E}[\|\widehat{f}_K - \mathbf{H}_K[G] \star \mathbf{P}[f]\|_{L_p(D)}^p] &= \mathbb{E}[\|\mathbf{H}_K[G] \star (\widehat{P} - \mathbf{P}[f])\|_{L_p(D)}^p] \\ &\leq 2^{Kp} \mathbb{E}[\|\widehat{P} - \mathbf{P}[f]\|_{L_p(D)}^p] \leq C 2^{Kp} n^{-\delta(s,p,\pi)p}, \end{aligned}$$

where C depends on $s, \pi, p, M, \varphi, \psi$.

To bound the second term in (26) we use the fixed point theorem's approximation. First we have to relate the L_p norm with the Besov norm. The triangle inequality and Lemma 1 ensure that if f is in $\mathcal{G}(s, \pi, M)$ then $\mathbf{H}_K[G] \star \mathbf{P}[f] - f$ is in $\mathcal{G}(s, \pi, M)$. It follows from the definition of the Besov norm that

$$\|\mathbf{H}_K[G] \star \mathbf{P}[f] - f\|_{L_p(D)} \leq \|\mathbf{H}_K[G] \star \mathbf{P}[f] - f\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)}.$$

We now use the approximation given by the Banach fixed point theorem

$$\|\mathbf{H}_K[G] \star \mathbf{P}[f] - f\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \leq (2\alpha)^K \|\mathbf{H}_1[G] \star \mathbf{P}[f] - \mathbf{P}[f]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)}.$$

After replacing $\mathbf{H}_1[G] \star \mathbf{P}[f]$ by its expression, using Lemma 1, the triangle inequality and Young's inequality we have

$$\|\mathbf{H}_1[G] \star \mathbf{P}[f] - \mathbf{P}[f]\|_{\mathcal{B}_{\pi\infty}^s(\mathbb{R}^d)} \leq 2\alpha M,$$

which leads to

$$(28) \quad \|\mathbf{H}_K[G] \star \mathbf{P}[f] - f\|_{L_p(D)} \leq (2\alpha)^{K+1} M.$$

We conclude by injecting (27), (28) into (26). The proof of Theorem 1 is now complete.

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