Quantitative Approximation by Multiple sigmoids Kantorovich-Shilkret quasi-interpolation neural network operators

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Abstract

In this article we derive multivariate quantitative approximation by Kantorovich-Shilkret type quasi-interpolation neural network operators with respect to supremum and L_p norms. This is done with rates using the multivariate modulus of continuity. We approximate continuous and bounded functions on \mathbb{R}^N , $N \in \mathbb{N}$. When they are also uniformly continuous we have pointwise and uniform convergences, plus L_p estimates. We include also the related Complex approximation. Our activation functions are induced by multiple general sigmoid functions.

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1 Introduction

The author in [1] and [2], see Chapters 2-5, was the first to establish neural network approximations to continuous functions with rates by very specifically defined neural network operators of Cardaliaguet-Euvrard and "Squashing" types, by employing the modulus of continuity of the engaged function or its high order derivative, and producing very tight Jackson type inequalities. He treats there both the univariate and multivariate cases. The defining these operators "bellshaped" and "squashing" functions are assumed to be compact support. Also

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in [2] he gives the *N*th order asymptotic expansion for the error of weak approximation of these two operators to a special natural class of smooth functions, see Chaptes 4-5 there.

The author inspired by [16], continued his studies on neural networks approximation by introducing and using the proper quasi-interpolation operators of sigmoidal and hyperbolic tangent type which resulted into [3] - [7], by treating both the univariate and multivariate cases. He did also the corresponding fractional case [8]. For recent works see [9] - [15].

The author here performs multivariate multiple general sigmoid activation functions based neural network approximation to continuous functions over the whole \mathbb{R}^N , $N \in \mathbb{N}$, then he extends his results to complex valued functions. L_p approximations are included. All convergences here are with rates expressed via the modulus of continuity of the involved function and given by very tight Jackson type inequalities.

The author comes up with the "right" precisely defined flexible quasi-interpolation, Kantorovich-Shilkret type integral coefficient neural networks operators associated with: multiple general sigmoid activation functions. In preparation to prove our results we present important properties of the general density functions defining our operators.

Feed-forward neural networks (FNNs) with one hidden layer, the only type of networks we deal with in this article, are mathematically expressed as

$$N_n(x) = \sum_{j=0}^n c_j \sigma\left(\langle a_j \cdot x \rangle + b_j\right), \ x \in \mathbb{R}^s, s \in \mathbb{N},$$

where for $0 \leq j \leq n$, $b_j \in \mathbb{R}$ are the thresholds, $a_j \in \mathbb{R}^s$ are the connection weights, $c_j \in \mathbb{R}$ are the coefficients, $\langle a_j \cdot x \rangle$ is the inner product of a_j and x, and σ is the activation function of the network. In many fundamental neural network models, the activation functions are based on multiple general sigmoid activation functions. About neural networks in general read [17], [18], [19].

In recent years non-additive integrals, like the N. Shilkret one [20], have become fashionable and more useful in Economics, etc.

2 Background

2.1 About Shilkret integral

Here we follow [20].

Let \mathcal{F} be a σ -field of subsets of an arbitrary set Ω . An extended non-negative real valued function μ on \mathcal{F} is called maximize if $\mu(\emptyset) = 0$ and

$$\mu\left(\cup_{i\in I} E_i\right) = \sup_{i\in I} \mu\left(E_i\right),\tag{1}$$

where the set I is of cardinality at most countable. We also call μ a maxitive measure. Here f stands for a non-negative measurable function on Ω . In [20], Niel Shilkret developed his non-additive integral defined as follows:

$$(N^*) \int_D f d\mu := \sup_{y \in Y} \left\{ y \cdot \mu \left(D \cap \{ f \ge y \} \right) \right\},$$
(2)

where Y = [0, m] or Y = [0, m) with $0 < m \le \infty$, and $D \in \mathcal{F}$. Here we take $Y = [0, \infty)$.

It is easily proved that

$$(N^*) \int_D f d\mu = \sup_{y>0} \left\{ y \cdot \mu \left(D \cap \{f > y\} \right) \right\}.$$
(3)

The Shilkret integral takes values in $[0, \infty]$.

The Shilkret integral ([20]) has the following properties:

$$(N^*)\int_{\Omega}\chi_E d\mu = \mu(E)\,,\tag{4}$$

where χ_E is the indicator function on $E \in \mathcal{F}$,

$$(N*)\int_{D} cfd\mu = c\left(N^{*}\right)\int_{D} fd\mu, \quad c \ge 0,$$
(5)

$$(N^*) \int_D \sup_{n \in \mathbb{N}} f_n d\mu = \sup_{n \in \mathbb{N}} (N^*) \int_D f_n d\mu, \tag{6}$$

where $f_n, n \in \mathbb{N}$, is an increasing sequence of elementary (countably valued) functions converging uniformly to f. Furthermore we have

$$(N^*)\int_D f d\mu \ge 0,\tag{7}$$

$$f \ge g \text{ implies } (N^*) \int_D f d\mu \ge (N^*) \int_D g d\mu, \tag{8}$$

where $f, g: \Omega \to [0, \infty]$ are measurable.

Let $a \leq f(\omega) \leq b$ for almost every $\omega \in E$, then

$$\begin{aligned} a\mu\left(E\right) &\leq \left(N^{*}\right) \int_{E} f d\mu \leq b\mu\left(E\right); \\ &\left(N^{*}\right) \int_{E} 1 d\mu = \mu\left(E\right); \end{aligned}$$

f > 0 almost everywhere and $(N^*) \int_E f d\mu = 0$ imply $\mu(E) = 0$; $(N^*) \int_{\Omega} f d\mu = 0$ if and only f = 0 almost everywhere; $(N^*) \int_{\Omega} f d\mu < \infty$ implies that

$$\overline{N}(f) := \{ \omega \in \Omega | f(\omega) \neq 0 \} \text{ has } \sigma \text{-finite measure;}$$
(9)

$$(N^{*}) \int_{D} (f+g) d\mu \leq (N^{*}) \int_{D} f d\mu + (N^{*}) \int_{D} g d\mu;$$
$$\left| (N^{*}) \int_{D} f d\mu - (N^{*}) \int_{D} g d\mu \right| \leq (N^{*}) \int_{D} |f-g| d\mu.$$
(10)

and

From now on in this article we assume that
$$\mu : \mathcal{F} \to [0, +\infty)$$
.

2.2 On activation functions

Let $i = 1, ..., N \in \mathbb{N}$ and $h_i : \mathbb{R} \to [-1, 1]$ be a general sigmoid function, such that it is strictly increasing, $h_i(0) = 0$, $h_i(-x) = -h_i(x)$, $h_i(+\infty) = 1$, $h_i(-\infty) = -1$. Also h_i is strictly convex over $(-\infty, 0]$ and strictly concave over $[0, +\infty)$, with $h_i^{(2)} \in C(\mathbb{R}, [-1, 1])$.

Some examples of related sigmoid functions follow: $\frac{1}{1+e^{-x}}$; $\tanh x$; $\frac{2}{\pi} \arctan\left(\frac{\pi}{2}x\right)$; $\frac{x}{\sqrt{1+x^{2m}}}$, $m \in \mathbb{N}$; $\frac{4}{\pi}gd\left(x\right)$; $\frac{x}{(1+|x|)^{\frac{1}{\lambda}}}$, λ is odd; $erf\left(\frac{\sqrt{\pi}}{2}x\right)$; $\frac{1}{1+e^{-\mu x}}$, $\tanh \mu x$, $\mu > 0$; for all $x \in \mathbb{R}$.

We consider the activation function

$$\psi_i(x) := \frac{1}{4} \left(h_i(x+1) - h_i(x-1) \right), \ x \in \mathbb{R}, \ i = 1, ..., N.$$
(11)

As in [11], p. 285, we get that $\psi_i(-x) = \psi_i(x)$, thus ψ_i is an even function. Since x + 1 > x - 1, then $h_i(x + 1) > h_i(x - 1)$, and $\psi_i(x) > 0$, all $x \in \mathbb{R}$.

We see that

$$\psi_i(0) = \frac{h_i(1)}{2}, \quad i = 1, ..., N.$$
 (12)

Let x > 1, we have that

$$\psi_i'(x) = \frac{1}{4} \left(h_i'(x+1) - h_i'(x-1) \right) < 0,$$

by h'_i being strictly decreasing over $[0, +\infty)$.

Let now 0 < x < 1, then 1 - x > 0 and 0 < 1 - x < 1 + x. It holds $h'_i(x-1) = h'_i(1-x) > h'_i(x+1)$, so that again $\psi'_i(x) < 0$. Consequently ψ_i is stritly decreasing on $(0, +\infty)$.

Clearly, ψ_i is strictly increasing on $(-\infty, 0)$, and $\psi'_i(0) = 0$. See that

$$\lim_{x \to +\infty} \psi_i(x) = \frac{1}{4} \left(h_i(+\infty) - h_i(+\infty) \right) = 0, \tag{13}$$

and

$$\lim_{x \to -\infty} \psi_i(x) = \frac{1}{4} \left(h_i(-\infty) - h_i(-\infty) \right) = 0.$$
 (14)

That is the x-axis is the horizontal asymptote on ψ_i .

Conclusion, ψ is a bell symmetric function with maximum

$$\psi_i\left(0\right) = \frac{h_i\left(1\right)}{2}.$$

We need

Theorem 1 We have that

$$\sum_{i=-\infty}^{\infty} \psi_i \left(x - i \right) = 1, \ \forall \ x \in \mathbb{R}, \ i = 1, ..., N.$$
(15)

Proof. As exactly the same as in [11], p. 286 is omitted. ■

Theorem 2 It holds

$$\int_{-\infty}^{\infty} \psi_i(x) \, dx = 1, \quad i = 1, ..., N.$$
 (16)

Proof. Similar to [11], p. 287. It is omitted. Thus $\psi_i(x)$ is a density function on \mathbb{R} , i = 1, ..., N. We need also

Theorem 3 Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds

$$\sum_{\substack{k = -\infty \\ : |nx - k| \ge n^{1 - \alpha}}}^{\infty} \psi_i (nx - k) < \frac{\left(1 - h_i \left(n^{1 - \alpha} - 2\right)\right)}{2}, \ i = 1, ..., N.$$
(17)

Notice that

$$\lim_{n \to +\infty} \frac{\left(1 - h_i \left(n^{1 - \alpha} - 2\right)\right)}{2} = 0, \ i = 1, ..., N.$$

Proof. Similar to [13], as such is omitted. \blacksquare We make

Remark 4 We define

$$Z(x_1, ..., x_N) := Z(x) := \prod_{i=1}^N \psi_i(x_i), \quad x = (x_1, ..., x_N) \in \mathbb{R}^N, \ N \in \mathbb{N}.$$
(18)

It has the properties:

(i)

$$Z(x) > 0, \ \forall x \in \mathbb{R}^N,$$
(19)

$$\sum_{k=-\infty}^{\infty} Z\left(x-k\right) := \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} Z\left(x_1-k_1,\dots,x_N-k_N\right) =$$
$$\sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} \prod_{i=1}^{N} \psi_i\left(x_i-k_i\right) = \prod_{i=1}^{N} \left(\sum_{k_i=-\infty}^{\infty} \psi_i\left(x_i-k_i\right)\right) \stackrel{(5)}{=} 1.$$

Hence

$$\sum_{k=-\infty}^{\infty} Z\left(x-k\right) = 1.$$
 (20)

That is

$$\sum_{k=-\infty}^{\infty} Z(nx-k) = 1, \quad \forall x \in \mathbb{R}^N; \ n \in \mathbb{N}.$$
 (21)

And

$$\int_{\mathbb{R}^N} Z(x) \, dx = \int_{\mathbb{R}^N} \left(\prod_{i=1}^N \psi_i(x_i) \right) dx_1 \dots dx_N = \prod_{i=1}^N \left(\int_{-\infty}^\infty \psi_i(x_i) \, dx_i \right) \stackrel{(16)}{=} 1,$$
(22)

thus

$$\int_{\mathbb{R}^{N}} Z(x) \, dx = 1, \tag{23}$$

that is Z is a multivariate density function.

Here denote $x = (x_1, ..., x_N)$, $||x||_{\infty} := \max\{|x_1|, ..., |x_N|\}, x \in \mathbb{R}^N$, also set $\infty := (\infty, ..., \infty), -\infty := (-\infty, ..., -\infty)$ upon the multivariate context, $0 < \beta < 1$,

$$\sum_{\substack{k=-\infty\\ \left\{\frac{k}{\|\frac{k}{n}-x\|_{\infty} > \frac{1}{n^{\beta}}}} Z\left(nx-k\right) = \sum_{\substack{k_{1}=-\infty\\ \left\|\frac{k}{n}-x\right\|_{\infty} > \frac{1}{n^{\beta}}} \sum_{\substack{k_{1}=-\infty\\ \left\|\frac{k}{n}-x\right\|_{\infty} > \frac{1}{n^{\beta}}} \left(\sum_{\substack{k_{1}=-\infty\\ \left\{\frac{k_{1}}{|\frac{k}{n}-x|_{\infty} > \frac{1}{n^{\beta}}}} \psi_{i}\left(nx_{i}-k_{i}\right) \right) \right) \le (for \ some \ r \in \{1,...,N\})$$

$$\left(\prod_{\substack{i=1\\i\neq r}}^{N} \left(\sum_{\substack{k_{i}=-\infty\\ \left\|\frac{k}{n}-x\right\|_{\infty} > \frac{1}{n^{\beta}}}} \psi_{i}\left(nx_{i}-k_{i}\right)\right)\right) \left(\sum_{\substack{k_{r}=-\infty\\ \left|\frac{k_{r}}{n}-x_{r}\right| > \frac{1}{n^{\beta}}}} \psi_{r}\left(nx_{r}-k_{r}\right) = (24)$$

$$\sum_{\substack{k_{r}=-\infty\\ \left|\frac{k_{r}}{n}-x_{r}\right| > \frac{1}{n^{\beta}}}} \psi_{r}\left(nx_{r}-k_{r}\right) = \sum_{\substack{k_{r}=-\infty\\ \left|nx_{r}-k_{r}\right| > n^{1-\beta}}}^{\infty} \psi_{r}\left(nx_{r}-k_{r}\right) \stackrel{(17)}{<}$$

$$\frac{1 - h_r \left(n^{1-\beta} - 2 \right)}{2} \le \max_{i \in \{1, \dots, N\}} \left(\frac{1 - h_i \left(n^{1-\beta} - 2 \right)}{2} \right).$$

 $That \ is$

$$\sum_{\substack{k = -\infty \\ \left\|\frac{k}{n} - x\right\|_{\infty} > \frac{1}{n^{\beta}}}^{\infty}} Z\left(nx - k\right) < \max_{i \in \{1, \dots, N\}} \left(\frac{1 - h_i\left(n^{1 - \beta} - 2\right)}{2}\right), \quad (25)$$

 $0<\beta<1,\ n\in\mathbb{N}:n^{1-\beta}>2,\ \forall\ x\in\mathbb{R}^N.$

Denote by

$$\delta_N(\beta, n) := \max_{i \in \{1, \dots, N\}} \left(\frac{1 - h_i \left(n^{1 - \beta} - 2 \right)}{2} \right), \tag{26}$$

 $0<\beta<1.$

For $f \in C_B^+(\mathbb{R}^N)$ (continuous and bounded functions from \mathbb{R}^N into \mathbb{R}_+), we define the first modulus of continuity

$$\omega_1(f,\delta) := \sup_{\substack{x, y \in \mathbb{R}^N \\ \|x - y\|_{\infty} \le h}} |f(x) - f(y)|, \quad h > 0.$$
(27)

Given that $f \in C_U^+(\mathbb{R}^N)$ (uniformly continuous from \mathbb{R}^N into \mathbb{R}_+ , same definition for ω_1), we have that

$$\lim_{h \to 0} \omega_1(f,h) = 0. \tag{28}$$

When N = 1, ω_1 is defined as in (27) with $\|\cdot\|_{\infty}$ collapsing to $|\cdot|$ and has the property (28).

3 Main Results

We need

Definition 5 Let \mathcal{L} be the Lebesgue σ -algebra on \mathbb{R}^N , $N \in \mathbb{N}$, and the maxitive measure $\mu : \mathcal{L} \to [0, +\infty)$, such that for any $A \in \mathcal{L}$ with $A \neq \emptyset$, we get $\mu(A) > 0$.

For $f \in C_B^+(\mathbb{R}^N)$, we define the multivariate Kantorovich-Shilkret type neural network operators for any $x \in \mathbb{R}^N$:

$$T_{n}^{\mu}(f,x) = T_{n}^{\mu}(f,x_{1},...,x_{N}) :=$$

$$\sum_{k=-\infty}^{\infty} \left(\frac{(N^{*}) \int_{[0,\frac{1}{N}]^{N}} f\left(t + \frac{k}{n}\right) d\mu(t)}{\mu\left(\left[0,\frac{1}{n}\right]^{N}\right)} \right) Z(nx-k) =$$

$$\sum_{k_{1}=-\infty}^{\infty} \sum_{k_{2}=-\infty}^{\infty} \cdots \sum_{k_{N}=-\infty}^{\infty} \left(\frac{(N^{*}) \int_{0}^{\frac{1}{n}} \dots \int_{0}^{\frac{1}{n}} f\left(t_{1} + \frac{k_{1}}{n}, t_{2} + \frac{k_{2}}{n}, \dots, t_{N} + \frac{k_{N}}{n}\right) d\mu\left(t_{1}, \dots, t_{N}\right)}{\mu\left(\left[0, \frac{1}{n}\right]^{N}\right)} \right)$$

$$(29)$$

$$\cdot \left(\prod_{i=1}^{N} \psi_{i}\left(nx_{i} - k_{i}\right)\right),$$

where $x = (x_1, ..., x_N) \in \mathbb{R}^N$, $k = (k_1, ..., k_N)$, $t = (t_1, ..., t_N)$, $n \in \mathbb{N}$. Clearly here $\mu\left(\left[0, \frac{1}{n}\right]^N\right) > 0, \forall n \in \mathbb{N}$. Above we notice that

$$||T_n^{\mu}(f)||_{\infty} \le ||f||_{\infty},$$
 (30)

so that $T_{n}^{\mu}(f, x)$ is well-defined.

We make

Remark 6 Let $t \in \left[0, \frac{1}{n}\right]^N$ and $x \in \mathbb{R}^N$, then

$$f\left(t+\frac{k}{n}\right) = f\left(t+\frac{k}{n}\right) - f\left(x\right) + f\left(x\right) \le \left|f\left(t+\frac{k}{n}\right) - f\left(x\right)\right| + f\left(x\right), \quad (31)$$

hence

$$(N^*) \int_{\left[0,\frac{1}{n}\right]^N} f\left(t + \frac{k}{n}\right) d\mu\left(t\right) \leq (N^*) \int_{\left[0,\frac{1}{n}\right]^N} \left| f\left(t + \frac{k}{n}\right) - f\left(x\right) \right| d\mu\left(t\right) + f\left(x\right) \mu\left(\left[0,\frac{1}{n}\right]^N\right).$$
(32)

That is

$$(N^*) \int_{\left[0,\frac{1}{n}\right]^N} f\left(t + \frac{k}{n}\right) d\mu\left(t\right) - f\left(x\right) \mu\left(\left[0,\frac{1}{n}\right]^N\right) \le$$

$$(N^*) \int_{\left[0,\frac{1}{n}\right]^N} \left| f\left(t + \frac{k}{n}\right) - f\left(x\right) \right| d\mu\left(t\right).$$
(33)

Similarly, we have

$$f(x) = f(x) - f\left(t + \frac{k}{n}\right) + f\left(t + \frac{k}{n}\right) \le \left|f\left(t + \frac{k}{n}\right) - f(x)\right| + f\left(t + \frac{k}{n}\right),$$

hence

$$(N^*) \int_{\left[0,\frac{1}{n}\right]^N} f(x) \, d\mu(t) \le (N^*) \int_{\left[0,\frac{1}{n}\right]^N} \left| f\left(t + \frac{k}{n}\right) - f(x) \right| \, d\mu(t) + (N^*) \int_{\left[0,\frac{1}{n}\right]^N} f\left(t + \frac{k}{n}\right) \, d\mu(t) \, .$$

 $That \ is$

$$f(x)\mu\left(\left[0,\frac{1}{n}\right]^{N}\right) - (N^{*})\int_{\left[0,\frac{1}{n}\right]^{N}}f\left(t + \frac{k}{n}\right)d\mu(t) \leq$$

$$(N^{*})\int_{\left[0,\frac{1}{n}\right]^{N}}\left|f\left(t + \frac{k}{n}\right) - f(x)\right|d\mu(t).$$
(34)

By (33) and (34) we derive

$$(N^*) \int_{\left[0,\frac{1}{n}\right]^N} f\left(t + \frac{k}{n}\right) d\mu\left(t\right) - f\left(x\right) \mu\left(\left[0,\frac{1}{n}\right]^N\right)\right| \le (N^*) \int_{\left[0,\frac{1}{n}\right]^N} \left| f\left(t + \frac{k}{n}\right) - f\left(x\right) \right| d\mu\left(t\right).$$

$$(35)$$

In particular it holds

$$\left| \frac{(N^*) \int_{[0,\frac{1}{n}]^N} f\left(t + \frac{k}{n}\right) d\mu\left(t\right)}{\mu\left(\left[0,\frac{1}{n}\right]^N\right)} - f\left(x\right) \right| \le \frac{(N^*) \int_{[0,\frac{1}{n}]^N} \left| f\left(t + \frac{k}{n}\right) - f\left(x\right) \right| d\mu\left(t\right)}{\mu\left(\left[0,\frac{1}{n}\right]^N\right)}.$$
(36)

We present the following approximation result.

Theorem 7 Let $f \in C_B^+(\mathbb{R}^N)$, $0 < \beta < 1$, $x \in \mathbb{R}^N$; $N, n \in \mathbb{N}$ with $n^{1-\beta} > 2$. Then i)

$$\sup_{\mu} |T_{n}^{\mu}(f,x) - f(x)| \le \omega_{1} \left(f, \frac{1}{n} + \frac{1}{n^{\beta}} \right) + 2 ||f||_{\infty} \delta_{N}(\beta,n) =: \lambda_{n}, \quad (37)$$

and

ii)

$$\sup_{\mu} \|T_n^{\mu}(f) - f\|_{\infty} \le \lambda_n.$$
(38)

Given that $f \in (C_U^+(\mathbb{R}^N) \cap C_B^+(\mathbb{R}^N))$, we obtain $\lim_{n \to \infty} T_n^{\mu}(f) = f$, uniformly. Above $\delta_N(\beta, n)$ is as in (26).

Proof. We observe that

$$|T_n^{\mu}(f,x) - f(x)| =$$

$$\sum_{k=-\infty}^{\infty} \left(\frac{(N^*) \int_{\left[0,\frac{1}{n}\right]^N} f\left(t + \frac{k}{n}\right) d\mu(t)}{\mu\left(\left[0,\frac{1}{n}\right]^N\right)} \right) Z\left(nx - k\right) - \sum_{k=-\infty}^{\infty} f\left(x\right) Z\left(nx - k\right) \right| =$$

proving the claim. \blacksquare

Additionally we give

Definition 8 Denote by $C_B^+(\mathbb{R}^N, \mathbb{C}) = \{f : \mathbb{R}^N \to \mathbb{C} | f = f_1 + if_2, where f_1, f_2 \in C_B^+(\mathbb{R}^N), N \in \mathbb{N}\}.$ We set for $f \in C_B^+(\mathbb{R}^N, \mathbb{C})$ that

$$T_n^{\mu}(f,x) := T_n^{\mu}(f_1,x) + i T_n^{\mu}(f_2,x), \qquad (41)$$

 $\forall \ n \in \mathbb{N}, \ x \in \mathbb{R}^N, \ i = \sqrt{-1}.$

Theorem 9 Let $f \in C_B^+(\mathbb{R}^N, \mathbb{C})$, $f = f_1 + if_2$, $N \in \mathbb{N}$, $0 < \beta < 1$, $x \in \mathbb{R}^N$; $n \in \mathbb{N}$ with $n^{1-\beta} > 2$. Then i) $\sup_{\mu} |T_n^{\mu}(f, x) - f(x)| \le \left[\omega_1\left(f_1, \frac{1}{n} + \frac{1}{n^{\beta}}\right) + \omega_1\left(f_2, \frac{1}{n} + \frac{1}{n^{\beta}}\right)\right]$

$$+2(\|f_1\|_{\infty} + \|f_2\|_{\infty})\delta_N(\beta, n) =: l_n,$$
(42)

and

ii)

$$\sup_{\mu} \|T_n^{\mu}(f) - f\| \le l_n.$$
(43)

Proof.

$$\begin{aligned} |T_{n}^{\mu}(f,x) - f(x)| &= |T_{n}^{\mu}(f_{1},x) + i \ T_{n}^{\mu}(f_{2},x) - f_{1}(x) - if_{2}(x)| = \\ |(T_{n}^{\mu}(f_{1},x) - f_{1}(x)) + i (T_{n}^{\mu}(f_{2},x) - f_{2}(x))| &\leq \\ |T_{n}^{\mu}(f_{1},x) - f_{1}(x)| + |T_{n}^{\mu}(f_{2},x) - f_{2}(x)| &\leq \\ \left(\omega_{1}\left(f_{1},\frac{1}{n} + \frac{1}{n^{\beta}}\right) + 2 \|f_{1}\|_{\infty} \delta_{N}(\beta,n)\right) + \\ \left(\omega_{1}\left(f_{2},\frac{1}{n} + \frac{1}{n^{\beta}}\right) + 2 \|f_{2}\|_{\infty} \delta_{N}(\beta,n)\right) = \\ \left[\omega_{1}\left(f_{1},\frac{1}{n} + \frac{1}{n^{\beta}}\right) + \omega_{1}\left(f_{2},\frac{1}{n} + \frac{1}{n^{\beta}}\right)\right] + \\ 2 (\|f_{1}\|_{\infty} + \|f_{2}\|_{\infty}) \delta_{N}(\beta,n). \end{aligned}$$
(45)

proving the claim. $\hfill\blacksquare$

We finish with an $L_{p_1}, p_1 \ge 1$, estimate.

Theorem 10 Let $f \in C_B^+(\mathbb{R}^N, \mathbb{C})$, $f = f_1 + if_2$, $N \in \mathbb{N}$, $0 < \beta < 1$, $n \in \mathbb{N}$ with $n^{1-\beta} > 2$, and $p_1 \ge 1$. Then

$$\|T_{n}^{\mu}(f) - f\|_{p_{1},\Lambda} \le l_{n} |\Lambda|^{\frac{1}{p_{1}}}, \qquad (46)$$

where $|\Lambda| < \infty$, is the Lebesgue measure of compact $\Lambda \subset \mathbb{R}^N$, and l_n as in (42).

Proof. By integrating (42), etc. \blacksquare

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