# SAMPLING THEORY IN ABSTRACT REPRODUCING KERNEL HILBERT SPACE

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ABSTRACT. Let H be a separable Hilbert space and k(t) an H-valued function on a subset  $\Omega$  of the real line  $\mathbb{R}$  such that  $\{k(t) \mid t \in \Omega\}$  is total in H. Then

$$\{f_x(t) := \langle x, k(t) \rangle_H \,|\, x \in H\}$$

becomes a reproducing kernel Hilbert space (RKHS) in a natural way. Here, we develop a sampling formula for functions in this RKHS, which generalizes the well-known celebrated Whittaker-Shannon-Kotel'nikov sampling formula in the Paley-Wiener space of band-limited signals. To be more precise, we develop a multi-channel sampling formula in which each channel is given rather arbitrary sampling rate. We also discuss the stability and oversampling.

# 1. INTRODUCTION

Let f(t) be a band-limited signal with band region  $[-\pi, \pi]$ , that is, a squareintegrable function on  $\mathbb{R}$  of which the Fourier transform  $\hat{f}$  vanishes outside  $[-\pi, \pi]$ . Then f can be recovered by its uniformly spaced discrete values as

$$f(t) = \sum_{n=-\infty}^{\infty} f(n) \frac{\sin \pi (t-n)}{\pi (t-n)},$$

which converges absolutely and uniformly over  $\mathbb{R}$ . This series is called the cardinal series or the Whittaker-Shannon-Kotel'nikov (WSK) sampling series. This formula tells us that once we know the values of a band-limited signal f at certain discrete points, we can recover f completely. In 1941, Hardy [4] recognized that this cardinal series is actually an orthogonal expansion.

WSK sampling series was generalized by Kramer [8] in 1957 as follows: Let  $k(\xi, t)$  be a kernel on  $I \times \Omega$ , where I is a bounded interval and  $\Omega$  is a subset of  $\mathbb{R}$ . Assume that  $k(\cdot, t) \in L^2(I)$  for each t in  $\Omega$  and there are points  $\{t_n\}_{n \in \mathbb{Z}}$  in  $\Omega$  such that  $\{k(\xi, t_n)\}$  is an orthonormal basis of  $L^2(I)$ . Then any  $f(t) = \int_I F(\xi)k(\xi, t)d\xi$  with  $F(\xi) \in L^2(I)$  can be expressed as a sampling series

$$f(t) = \sum_{n} f(t_n) \int_{I} k(\xi, t) \,\overline{k(\xi, t_n)} \, d\xi,$$

which converges absolutely and uniformly over the subset D on which  $||k(\cdot,t)||_{L^2(I)}$  is bounded. While WSK sampling series treats sample values taken at uniformly spaced points, Kramer's series may take sample values at nonuniformly spaced points.

Key words and phrases. Sampling, Reproducing Kernel Hilbert space, oversampling.

Recently, A. G. Garcia and A. Portal [3] extended the WSK and Kramer sampling formulas further to a more general setting using a suitable abstract Hilbert space valued kernel.

On the other hand, Papoulis [10] (see also [7]) introduced a multi-channel sampling formula for band-limited signals, in which a signal is recovered from discrete sample values of several transformed versions of the signal.

In this work, following the setting introduced by Garcia and Portal [3], we first extends and modify Theorem 1 in [3] into a single channel sampling formula (see Theorem 3.2 below), which is more transparent. It is then easy to extend it to a multi-channel sampling formula, in which each channel can be given rather arbitrary sampling rate. Comparing two-channel sampling formula, Theorem 3 in [3] and our multi-channel sampling formula, Theorem 3.3, reveals the advantage of modification made in Theorem 3.2. Finally, we also discuss the oversampling and recovery of missing samples in the single-channel sampling formula.

## 2. Preliminaries

For  $f(t) \in L^2(\mathbb{R})$ , we let

$$\mathcal{F}(f)(\xi) = \hat{f}(\xi) := \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-i\xi t} dt$$

be the Fourier transform of f(t) and

$$f(t) = \mathcal{F}^{-1}(\hat{f})(t) := \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \hat{f}(\xi) \, e^{i\xi t} \, d\xi$$

the inverse Fourier transform  $\hat{f}(\xi)$ .

**Definition 2.1.** For any w > 0, the Paley-Wiener space  $PW_{\pi w}$  is defined to be

 $PW_{\pi w} := \{ f \mid f \in L^2(\mathbb{R}), \ supp \ \widehat{f} \in [-\pi w, \pi w] \}.$ 

Note that  $PW_{\pi w}$  is isometrically isomorphic onto  $L^2[-\pi w, \pi w]$  under the Fourier transform.

We call a basis  $\{\varphi_n\}$  of a separable Hilbert space H to be an unconditional basis of H if for every  $f \in H$ , the expansion  $f = \sum c_n(f)\varphi_n$  still converges to f after any permutation of its terms. We also call a basis  $\{\varphi_n\}$  to be a Riesz basis of H if there is a linear isomorphism T from H onto H such that  $T(e_n) = \varphi_n$  where  $\{e_n\}$ is an orthonormal basis for H. Then any Riesz basis of H is an unconditional basis of H but not conversely in general.

**Definition 2.2.** [12] A Hilbert space H consisting of complex-valued functions defined on a set  $D \neq \emptyset$  is called a reproducing kernel Hilbert space (RKHS in short) if there exists a function k(s,t) on  $D \times D$  satisfying

- (1)  $k(\cdot, t) \in H$  for each  $t \in D$ ;
- (2)  $\langle f(s), k(s,t) \rangle_H = f(t)$  for all  $f \in H$  and all  $t \in D$ .

Such a function k(s,t) is called a reproducing kernel of H.

We need some properties of RKHS's.

**Proposition 2.3.** [5] Let H be a Hilbert space as in Definition 2.2. Then we have:

(a) *H* is an RKHS if and only if the point evaluation map  $l_t(f) := f(t)$  is a bounded linear functional on *H* for each  $t \in D$ ;

- (b) an RKHS H has a unique reproducing kernel;
- (c) the convergence of a sequence in an RKHS H implies its uniform convergence over any subset of D on which k(t,t) is bounded.

For example, the Paley-Wiener space  $PW_{\pi w}$  is an RKHS with the reproducing kernel  $k(s,t) = w \frac{\sin \pi w(s-t)}{\pi w(s-t)}$ .

#### 3. Multi-Channel Sampling

Let H be a separable Hilbert space and  $k : \Omega \longrightarrow H$  be an H-valued function on a subset  $\Omega$  of the real line  $\mathbb{R}$ . Define a linear operator T on H by

$$T(x)(t) = f_x(t) := \langle x, k(t) \rangle_H, \ t \in \Omega.$$

We call k(t) the kernel of the linear operator T.

# Lemma 3.1. ([3])

(a) T is one-to-one if and only if  $\{k(t) \mid t \in \Omega\}$  is total in H.

Assume  $\{k(t) \mid t \in \Omega\}$  is total in H so that  $T: H \longrightarrow T(H)$  is a bijection. Then

(b)  $\langle T(x), T(y) \rangle_{T(H)} := \langle x, y \rangle_H$  defines an inner product on T(H), with which T(H) is a Hilbert space and  $T: H \longrightarrow T(H)$  is unitary. Moreover, T(H) becomes an RKHS with the reproducing kernel  $k(s,t) := \langle k(t), k(s) \rangle_H$ .

*Proof.* (a) T is one-to-one if and only if  $\{k(t) \mid t \in \Omega\}^{\perp} = \{0\}$  if and only if  $\overline{span}\{k(t) \mid t \in \Omega\} = H$ , that is,  $\{k(t) \mid t \in \Omega\}$  is total in H.

(b) It is trivial that  $\langle T(x), T(y) \rangle_{T(H)} := \langle x, y \rangle_H$  defines an inner product on T(H) with which  $T : H \longrightarrow T(H)$  is unitary. Now for any  $f(\cdot) = \langle x, k(\cdot) \rangle_H$  in T(H) and  $t \in \Omega$ ,

$$|f(t)| = |\langle x, k(t) \rangle_H| \le ||x||_H ||k(t)||_H = ||f||_{T(H)} ||k(t)||_H$$

so that  $l_t(f) = f(t)$  is a bounded linear functional on T(H). Hence T(H) is an RKHS by Proposition 2.3. Since

$$f(t) = \langle x, k(t) \rangle_H = \langle T(x)(s), T(k(t))(s) \rangle_{T(H)} = \langle f(s), \langle k(t), k(s) \rangle_H \rangle_{T(H)},$$

the reproducing kernel k(s,t) of T(H) is  $\langle k(t), k(s) \rangle_H$ .

First, we develop a single-channel sampling formula. Let  $\tilde{k} : \Omega \longrightarrow H$  be another H-valued function on  $\Omega$  and  $\tilde{T}$  the linear operator on H defined by

$$T(x)(t) = \hat{f}_x(t) = \langle x, \hat{k}(t) \rangle_H.$$

**Theorem 3.2.** If  $KerT \subseteq Ker\widetilde{T}$  and there exists a sequence  $\{t_n\}$  in  $\Omega$  such that  $\{\tilde{k}(t_n)\}_n$  is a basis of H, then T is one-to-one so that T(H) becomes an RKHS under the inner product  $\langle T(x), T(y) \rangle_{T(H)} := \langle x, y \rangle_H$ . Moreover, there is a basis  $\{S_n(t)\}_n$  of T(H) with which we have the sampling expansion:

$$f_x(t) = \sum_n \tilde{f}_x(t_n) S_n(t), \qquad f_x(t) \in T(H)$$
(3.1)

which converges not only in T(H) but also uniformly over any subset on which  $||k(t)||_{H}$  is bounded.

*Proof.* Assume  $\widetilde{T}(x)(t) = \langle x, \tilde{k}(t) \rangle = 0$  on  $\Omega$ . Then  $\langle x, \tilde{k}(t_n) \rangle = 0$  for any n so that x = 0 since  $\{\tilde{k}(t_n)\}_n$  is a basis of H. Hence  $KerT = Ker\widetilde{T} = \{0\}$  and T(H) becomes an RKHS as in Lemma 3.1 (b).

Let  $\{x_n\}_n = \{\tilde{k}(t_n)\}_n$  and  $\{x_n^*\}_n$  be its dual. Then  $\{T(x_n)(t)\}$  and  $\{T(x_n^*)(t)\}$  are bases of T(H), which are dual each other since T is unitary.

Expanding any  $f_x(t) = T(x)(t)$  in T(H) via the basis  $\{S_n(t)\}_n = \{T(x_n^*)(t)\}$  gives

$$f_x(t) = \sum_n \langle T(x), T(x_n) \rangle_{T(H)} S_n(t) = \sum_n \langle x, x_n \rangle_H S_n(t)$$
$$= \sum_n \langle x, \tilde{k}(t_n) \rangle_H S_n(t) = \sum_n \tilde{f}_x(t_n) S_n(t).$$

Uniform convergence of the series (3.1) follows from Proposition 2.3 (c).

The single channel sampling expansion (3.1) may not converge absolutely unless  $\{x_n\}_n$  is an unconditional basis and may not be stable. However, if  $\{x_n\}_n$  is an unconditional basis and  $\sup_n ||x_n^*|| < \infty$ , then (3.1) is a stable sampling expansion, which converges absolutely on  $\Omega$ . In fact, if then,  $\{S_n(t)\}_n$  becomes an unconditional basis of T(H) and  $\sup_n ||S_n(t)|| = \sup_n ||x_n^*|| < \infty$ . Since  $\{\frac{1}{||S_n(t)||}S_n(t)\}_n$  is a Riesz basis of T(H) by the Köthe-Toeplitz Theorem [9], there is a constant B > 0 such that

$$||f_x(t)||^2_{T(H)} \le B \sum_n |\tilde{f}_x(t_n)|^2 ||S_n(t)||^2 \le (\sup_n ||S_n(t)||)^2 B \sum_n |\tilde{f}_x(t_n)|^2, \quad f_x(t) \in T(H)$$

Furthermore, the sampling series expansion (3.1) remains valid when  $\{\tilde{k}(t_n)\}_n$  is not a basis but a frame of H. When  $\tilde{k}(t) = k(t)$  on  $\Omega$  so that  $T = \tilde{T}$ , Theorem 3.2 is essentially Theorem 1 in [3]. However, Theorem 3.2 might have some advantage over Theorem 1 in [3]. While Theorem 1 in [3] requires first the expansion of the kernel k(t) in terms of a given basis of H and then the interpolatory condition for the expansion coefficients at some points in  $\Omega$ , Theorem 3.2 simply requires points in  $\Omega$ , of which values under  $k(\cdot)$  form a basis of H.

Now, we can extend Theorem 3.2 naturally to a multi-channel setting. Let  $\{k_i\}_{i=1}^N$  be N H-valued functions on  $\Omega$  and  $\{T_i\}_{i=1}^N$  linear operators on H defined by

$$T_i(x)(t) = f_x^i(t) := \langle x, k_i(t) \rangle_H, \quad x \in H.$$

**Theorem 3.3.** (Asymmetric nonuniform multi-channel sampling formula) If  $KerT \subseteq \bigcap_{i=1}^{N} KerT_i$  and there exist points  $\{t_{i,n} \mid 1 \leq i \leq N, n \in \mathbb{Z}\} \subset \Omega$  and constants  $\{\alpha_{i,n}^j \mid 1 \leq i \leq N, 1 \leq j \leq M \text{ and } n \in \mathbb{Z}\}$  for some integer  $M \geq 1$  such that  $\{\sum_{i=1}^{N} \alpha_{i,n}^j k_i(t_{i,n}) \mid 1 \leq j \leq M \text{ and } n \in \mathbb{Z}\}$  is an unconditional basis of H, then there is a basis  $\{S_{j,n}(t) \mid 1 \leq j \leq M \text{ and } n \in \mathbb{Z}\}$  of T(H) such that for any  $f_x(t) = T(x)(t) \in T(H)$ ,

$$f_x(t) = \sum_{n \in \mathbb{Z}} \sum_{j=1}^M \{ \overline{\alpha_{1,n}^j} f_x^1(t_{1,n}) + \overline{\alpha_{2,n}^j} f_x^2(t_{2,n}) + \dots + \overline{\alpha_{N,n}^j} f_x^N(t_{N,n}) \} S_{j,n}(t) \quad (3.2)$$

which converges in T(H). Moreover, the series (3.2) converges absolutely and uniformly on any subset of  $\Omega$  over which  $||k(t)||_H$  is bounded.

*Proof.* First, we prove that T is one-to-one. Suppose  $T(x)(t) = \langle x, k(t) \rangle = 0$  for all  $t \in \Omega$ . Then,  $\langle x, k_i(t) \rangle = 0, 1 \le i \le N$  on  $\Omega$  since  $KerT \subseteq \bigcap_{i=1}^{N} KerT_i$ . In particular,  $\langle x, \sum_{i=1}^{N} \alpha_{i,n}^{j} k_i(t_{i,n}) \rangle = 0$  for all  $1 \le j \le M$  and  $n \in \mathbb{Z}$  so that x = 0 since  $\{\sum_{i=1}^{N} \alpha_{i,n}^{j} k_{i}(t_{i,n}) \mid 1 \leq j \leq M \text{ and } n \in \mathbb{Z}\}$  is a basis of H. Therefore,  $T: H \longrightarrow T(H)$  is a bijection and T(H) becomes an RKHS under the inner product

 $\begin{array}{l} \langle T(x), T(y) \rangle_{T(H)} & \coloneqq \text{objection and } T(H) \text{ becomes an terms under the inner product} \\ \langle T(x), T(y) \rangle_{T(H)} & \coloneqq \langle x, y \rangle_{H} \text{ by Lemma 3.1.} \\ & \text{Let } x_{n}^{j} \coloneqq \sum_{i=1}^{N} \alpha_{i,n}^{j} k_{i}(t_{i,n}) \text{ for } 1 \leq j \leq M \text{ and } n \in \mathbb{Z} \text{ and } \{x_{n}^{j*}\}_{j=1,n\in\mathbb{Z}}^{M} \text{ be the } \\ & \text{dual of } \{x_{n}^{j}\}. \text{ Then, } \{T(x_{n}^{j})\}_{j=1,n\in\mathbb{Z}}^{M} \text{ becomes an unconditional basis of } T(H) \text{ with } \\ & \text{the dual basis } \{T(x_{n}^{j*})\}_{j=1,n\in\mathbb{Z}}^{M} \coloneqq \{S_{j,n}(t)\}_{j=1,n\in\mathbb{Z}}^{M}, \text{ which is also unconditional.} \\ & \text{Expanding } f_{x}(t) = T(x)(t) \text{ in } T(H) \text{ with respect to } \{S_{j,n}(t)\}_{j=1,n\in\mathbb{Z}}^{M}, \text{ we have } \end{array}$ 

$$f(t) = \sum_{n \in \mathbb{Z}} \sum_{j=1}^{M} \langle T(x), T(x_n^j) \rangle_{T(H)} S_{j,n}(t)$$
  
$$= \sum_{n \in \mathbb{Z}} \sum_{j=1}^{M} \langle x, x_n^j \rangle_H S_{j,n}(t)$$
  
$$= \sum_{n \in \mathbb{Z}} \sum_{j=1}^{M} \{ \overline{\alpha_{1,n}^j} f_x^1(t_{1,n}) + \dots + \overline{\alpha_{N,n}^j} f_x^N(t_{N,n}) \} S_{j,n}(t).$$

Uniform convergence of the series (3.2) follows from Proposition 2.3 (c). Finally, the series (3.2) converges also absolutely since it is an unconditional basis expansion. П

If either  $KerT = \{0\}$  or  $k_i(t) = A_i(k(t)), 1 \le i \le N$ , where  $A_i$ 's are automorphisms of H, then the first assumption  $KerT \subseteq \bigcap_{i=1}^{N} KerT_i$  of Theorem 3.3 is trivially satisfied. For example, it is so when  $H = L^2[-\pi,\pi]$ ,  $\Omega = \mathbb{R}$  and  $k(t) = \frac{e^{-it\xi}}{\sqrt{2\pi}}$ so that  $T = \mathcal{F}^{-1}$  is the inverse Fourier to  $\mathcal{F}$ . so that  $T = \mathcal{F}^{-1}$  is the inverse Fourier transform. In particular, if N = M = 2,  $k_1(t) = k(t), t_{1,n} = t_{2,n} = t_n$ , and  $\{\alpha_{1,n}^1 k(t_n) + \alpha_{2,n}^1 k_2(t_n)\} \cup \{\alpha_{1,n}^2 k(t_n) + \alpha_{2,n}^2 k_2(t_n)\}$ is a Riesz basis of H, then Theorem 3.3 is essentially the same as Theorem 3 in [3]. When  $H = L^2[-\pi w, \pi w](w > 0), \Omega = \mathbb{R}$  and

$$k(t) = \frac{1}{\sqrt{2\pi}} e^{-it\xi}, \ k_i(t) = \frac{1}{\sqrt{2\pi}} \overline{A_i(\xi)} e^{-it\xi} \quad (1 \le i \le N)$$

for suitable bounded measurable functions  $A_i(\xi)(1 \leq i \leq N)$  on  $[-\pi w, \pi w]$ , we have

$$T(\phi)(t) = \frac{1}{\sqrt{2\pi}} \int_{-\pi w}^{\pi w} \phi(\xi) e^{it\xi} d\xi = \mathcal{F}^{-1}(\phi)(t)$$
  
$$T_i(\phi)(t) = \frac{1}{\sqrt{2\pi}} \int_{-\pi w}^{\pi w} A_i(\xi) \phi(\xi) e^{it\xi} d\xi = \mathcal{F}^{-1}(A_i\phi)(t) \quad (1 \le i \le N).$$

Hence, T(H) becomes the Paley-Wiener space  $PW_{\pi w}$  and then Theorem 3.3 reduces to an asymmetric multi-channel sampling handled in [7].

If  $\{\sum_{i=1}^{N} \alpha_{i,n}^{j} k_{i}(t_{i,n}) | 1 \leq j \leq M \text{ and } n \in \mathbb{Z}\}$  is a frame of H in Theorem 3.3, then the sampling series expansion (3.2) still holds.

As in the single channel case, if  $\sup_{i,j,n} \|\alpha_{i,n}^j x_n^{j*}\| < \infty$ , then the multi-channel sampling expansion (3.2) is also stable in the following sense.

**Definition 3.4.** (cf. Rawn [11] and Yao and Thomas [13]) We say that  $\{t_{i,n} | 1 \leq t_{i,n} \}$  $i \leq N$  and  $n \in \mathbb{Z}$  is a set of stable sampling for T(H) if there exists A > 0 which is independent of  $f \in T(H)$  such that

$$||f(t)||_{T(H)}^2 \le A \sum_{n=-\infty}^{\infty} \sum_{i=1}^{N} |f_x^i(t_{i.n})|^2 \quad f \in T(H).$$

Let B > 0 be the upper Riesz bound for the Riesz basis  $\{\frac{1}{\|S_{j,n}\|}S_{j,n}(t)\}$  of T(H). Then

$$\|f_x\|_{T(H)}^2 \le B \sum_n \sum_{j=1}^M \sum_{i=1}^N |\overline{\alpha_{i,n}^j} f_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|\alpha_{i,n}^j S_{j,n}\|)^2 BM \sum_n \sum_{i=1}^N |f_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|\alpha_{i,n}^j S_{j,n}\|)^2 BM \sum_n \sum_{i=1}^N |G_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|\alpha_{i,n}^j S_{j,n}\|)^2 BM \sum_n \sum_{i=1}^N |G_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|\alpha_{i,n}^j S_{j,n}\|)^2 BM \sum_n \sum_{i=1}^N |G_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|\alpha_{i,n}^j S_{j,n}\|)^2 BM \sum_n \sum_{i=1}^N |G_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|\alpha_{i,n}^j S_{j,n}\|)^2 BM \sum_n \sum_{i=1}^N |G_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|\alpha_{i,n}^j S_{j,n}\|)^2 BM \sum_n \sum_{i=1}^N |G_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|\alpha_{i,n}^j S_{j,n}\|)^2 BM \sum_n \sum_{i=1}^N |G_x^i(t_{i,n})|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|G_x^i(t_{i,n})\|^2 \|S_{j,n}\|^2 \|S_{j,n}\|^2 \le (\sup_{i,j,n} \|G_x^i(t_{i,n})\|^2 \le (\bigcup_{i,j,n} \|G_x^i(t$$

so that (3.2) is a stable sampling expansion with respect to  $\{t_{i,n}\}$  when  $\sup \|\alpha_{i,n}^j x_n^{j*}\| < \infty$  $\infty$ .

We now discuss several examples in which we always take  $H = L^2[-\pi,\pi], \Omega = \mathbb{R}$  and  $k(t) = \frac{1}{\sqrt{2\pi}} e^{-it\xi}$  so that  $T = \mathcal{F}^{-1}$  is the inverse Fourier transform and  $T(H) = PW_{\pi}.$ 

### **Example 3.5** (Sampling with Hilbert transform).

Take  $\tilde{k}(t) = i \operatorname{sgn}(\xi) k(t)$  so that  $\widetilde{T}(f)(t) = \widetilde{f}(t)$  is the Hilbert transform of f(t) in  $PW_{\pi}$ . Choosing  $\{t_n\}_{n\in\mathbb{Z}} = \{n\}_{n\in\mathbb{Z}}, \{x_n\}_{n\in\mathbb{Z}} = \{i\operatorname{sgn}\xi \frac{e^{-in\xi}}{\sqrt{2\pi}}\}_{n\in\mathbb{Z}}$  is an orthonormal basis of  $L^2[-\pi,\pi]$  so that  $\{x_n^*\}_{n\in\mathbb{Z}} = \{x_n\}_{n\in\mathbb{Z}}$ . We then have

$$S_n(t) = \frac{1}{\sqrt{2\pi}} \int_{-\pi}^{\pi} i \operatorname{sgn}(\xi) \, \frac{e^{-in\xi}}{\sqrt{2\pi}} \, e^{it\xi} \, d\xi = -\operatorname{sinc} \frac{1}{2} \, (t-n) \sin \frac{\pi}{2} \, (t-n)$$

where sinct :=  $\frac{\sin \pi t}{\pi t}$ . Hence, we have

$$f(t) = -\sum_{n \in \mathbb{Z}} \tilde{f}(n) \operatorname{sinc} \frac{1}{2} (t-n) \sin \frac{\pi}{2} (t-n), \quad f(t) \in PW_{\pi}$$

Using the operational relation  $\tilde{\tilde{f}} = -f([5, \text{ Appendix B}])$  and the fact that if  $f \in$  $PW_{\pi}$ , then so does  $\tilde{f}$ , we also have

$$\tilde{f}(t) = \sum_{n \in \mathbb{Z}} f(n) \operatorname{sinc} \frac{1}{2} (t-n) \sin \frac{\pi}{2} (t-n), \quad f(t) \in PW_{\pi}.$$

**Example 3.6.** Here, we derive asymmetric derivative sampling formula on  $PW_{\pi}$ ,

in which we take samples from f(t) and f'(t) with ratio 2:1. Take  $k_1(t) = k(t) = \frac{1}{\sqrt{2\pi}}e^{-it\xi}$  and  $k_2(t) = -i\xi k(t) = k'(t)$  so that  $f^1(t) = f(t)$  and  $f^2(t) = f'(t)$  for  $f(t) \in PW_{\pi}$ . Now, take the set of sampling points  $\{t_{1,n} = \frac{3n}{2}\}_{n \in \mathbb{Z}} \text{ for } f_x^1(t) \text{ and } \{t_{2,n} = 3n\}_{n \in \mathbb{Z}} \text{ for } f_x^2(t). \text{ With } \alpha_{1,n}^1 = \sqrt{\frac{3}{2}}, \ \alpha_{2,n}^1 = \alpha_{1,n}^2 = 0 \text{ and } \alpha_{2,n}^2 = -\sqrt{3}, \ \{\alpha_{1,n}^1 \, k_1(t_{1,n}) + \alpha_{2,n}^1 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} \cup \ \{\alpha_{1,n}^2 \, k_1(t_{1,n}) + \alpha_{2,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} = 0 \text{ for } f_x^2(t) + \alpha_{1,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} = 0 \text{ for } f_x^2(t) + \alpha_{1,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} = 0 \text{ for } f_x^2(t) + \alpha_{1,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} + \alpha_{1,n}^2 \, k_2(t_{2,n}) + \alpha_{1,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} = 0 \text{ for } f_x^2(t) + \alpha_{1,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} + \alpha_{1,n}^2 \, k_2(t_{2,n}) + \alpha_{1,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} + \alpha_{1,n}^2 \, k_2(t_{2,n}) + \alpha_{1,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} + \alpha_{1,n}^2 \, k_2(t_{2,n}) + \alpha_{1,n}^2 \, k_2(t_{2,n}) + \alpha_{1,n}^2 \, k_2(t_{2,n}) + \alpha_{1,n}^2 \, k_2(t_{2,n})\}_{n \in \mathbb{Z}} + \alpha_{1,n}^2 \, k_2(t_{2,n}) + \alpha_{1,n$  $\alpha_{2,n}^2 k_2(t_{2,n})\}_{n \in \mathbb{Z}} = \{\sqrt{\frac{3}{4\pi}} e^{-i3n\xi/2}\}_{n \in \mathbb{Z}} \cup \{\sqrt{\frac{3}{2\pi}} i\xi e^{-i3n\xi}\}_{n \in \mathbb{Z}}$  is a Riesz basis of  $L^{2}[-\pi,\pi]$ , of which the dual (cf. [6]) is

$$\left\{\sqrt{\frac{3}{4\pi}}\,\mu_{1,n}(\xi)\,e^{-i3n\xi/2}\right\}\cup\left\{\sqrt{\frac{3}{2\pi}}\,\mu_{2}(\xi)\,e^{-i3n\xi}\right\},\quad n\in\mathbb{Z}$$
(3.3)

where

$$\mu_{1,n}(\xi) = \begin{cases} 3 (\xi + \pi)/2\pi, & \xi \in [-\pi, -\pi/3); \\ 1, & \xi \in [-\pi/3, \pi/3); \\ -3 (\xi - \pi)/2\pi, & \xi \in [\pi/3, \pi] \end{cases}$$

if n is even,

$$\mu_{1,n}(\xi) = \begin{cases} 1/2, & \xi \in [-\pi, -\pi/3); \\ 1, & \xi \in [-\pi/3, \pi/3); \\ 1/2, & \xi \in [\pi/3, \pi] \end{cases}$$

if n is odd, and

$$\mu_2(\xi) = \begin{cases} -3i/4\pi, & \xi \in [-\pi, -\pi/3); \\ 0, & \xi \in [-\pi/3, \pi/3); \\ 3i/4\pi, & \xi \in [\pi/3, \pi]. \end{cases}$$

Taking inverse Fourier transform on (3.3), we have a Riesz basis of  $PW_{\pi}$ :

$$S_{1,n}(t) = \begin{cases} \sqrt{\frac{2}{3}} \operatorname{sinc} \frac{1}{3} \left( t - \frac{3n}{2} \right) \operatorname{sinc} \frac{2}{3} \left( t - \frac{3n}{2} \right) & \text{if } n \text{ is even,} \\ \\ \sqrt{\frac{3}{8}} \left\{ \frac{1}{3} \operatorname{sinc} \frac{1}{3} \left( t - \frac{3n}{2} \right) + \operatorname{sinc} \left( t - \frac{3n}{2} \right) \right\} & \text{if } n \text{ is odd} \\ \\ S_{2,n}(t) = -\frac{\sqrt{3}}{2\pi} \operatorname{sinc} \frac{1}{3} \left( t - 3n \right) \operatorname{sin} \frac{2\pi}{3} \left( t - 3n \right). \end{cases}$$

With these setting we have the nonsymmetric derivative sampling formula:

$$f(t) = \sum_{n \in \mathbb{Z}} \sqrt{\frac{3}{2}} f(\frac{3n}{2}) S_{1,n}(t) - \sqrt{3} f'(3n) S_{2,n}(t), \quad f(t) \in PW_{\pi}.$$

**Example 3.7.** We now take  $k_1(t) = k(t) = \frac{1}{\sqrt{2\pi}}e^{-it\xi}$  and  $k_2(t) = e^{i\xi}k(t)$  so that  $f^1(t) = f(t)$  and  $f^2(t) = f(t-1)$ . We want to express  $f \in PW_{\pi}$  via samples from f(t) and f(t-1) with ratio 3 : 2. Note that  $\{\sqrt{\frac{5}{6\pi}}e^{-i5n\xi/3}\}_{n\in\mathbb{Z}}$  $\{\sqrt{\frac{5}{4\pi}}e^{i\xi}e^{-i5n\xi/2}\}_{n\in\mathbb{Z}}$  forms a Riesz basis of  $L^2[-\pi,\pi]$  with the dual  $\left\{\sqrt{\frac{5}{c}} \frac{1}{\frac{i4\pi}{5}} \frac{\mu_{1,n}(\xi)}{\mu_{1,n}(\xi)} e^{-i5n\xi/3}\right\}$ 

$$\left( \sqrt[]{6\pi} e^{-i4\pi/3} - e^{-i2\pi/3} + \mu_{2,n}(\xi) e^{i\xi} e^{-i5n\xi/2} \right)_{n\in\mathbb{Z}} \qquad (3.4)$$

where

$$\mu_{1,n}(\xi) = \begin{cases} e^{-i\frac{4}{5}\pi} + e^{-i2n\pi/3} + e^{-i\frac{6}{5}\pi} e^{i2n\pi/3}, & -\pi \le \xi < -\pi/5; \\ e^{-i\frac{4}{5}\pi} - e^{-i\frac{2}{5}\pi}, & -\pi/5 \le \xi < \pi/5; \\ -e^{-i\frac{2}{5}\pi} - e^{-i2n\pi/3} - e^{-i\frac{6}{5}\pi} e^{i2n\pi/3}, & \pi/5 \le \xi \le \pi \end{cases}$$

and

$$\mu_{2,n}(\xi) = \begin{cases} -(-1)^n e^{-i\frac{8}{5}\pi} - e^{-i\frac{2}{5}\pi}, & -\pi \le \xi < -\pi/5; \\ 0, & -\pi/5 \le \xi < \pi/5; \\ e^{-i\frac{4}{5}\pi} + (-1)^n e^{-i\frac{8}{5}\pi}, & \pi/5 \le \xi \le \pi. \end{cases}$$

Then, we can obtain the sampling series

$$f(t) = \sum_{n} \sqrt{\frac{5}{3}} f(\frac{5n}{3}) S_{1,n}(t) + \sqrt{\frac{5}{2}} f(\frac{5n}{2} - 1) S_{2,n}(t), \quad f(t) \in PW_{\pi},$$

where  $\{S_{1,n}(t)\} \cup \{S_{2,n}(t)\}$  are the inverse Fourier transforms of functions in (3.4).

## 4. Oversampling and reconstruction of missing samples

We now develop the oversampling expansion, which extends the one in Kramer [2]. We extend an oversampling expansion in Kramer's setting [2] to a more general case. Again, let k and  $\tilde{k} : \Omega \longrightarrow H$  be H-valued functions. Assume that there exists  $\{t_n\} \subset \Omega$  such that  $\{x_n := \tilde{k}(t_n)\}_n$  is a basis of H with the dual basis  $\{x_n^*\}_n$ . Define linear operators T and  $\tilde{T}$  on H by  $T(x)(t) = \langle x, k(t) \rangle_H := f_x(t)$  and  $\tilde{T}(x)(t) = \langle x, \tilde{k}(t) \rangle_H := \tilde{f}_x(t)$ , respectively and assume  $KerT \subseteq Ker\tilde{T}$ . Then, both T and  $\tilde{T}$  are one-to-one and so T(H) and  $\tilde{T}(H)$  become RKHS's.

Now, let G be a proper closed subspace of H and  $P: H \longrightarrow G$  the orthogonal projection onto G. Then, for any  $x \in G$  we have

$$x = \sum_{n} \langle x, \tilde{k}(t_n) \rangle_H x_n^2$$

so that

$$x = P(x) = \sum_{n} \langle x, \tilde{k}(t_n) \rangle_H P(x_n^*) = \sum_{n} \tilde{f}_x(t_n) P(x_n^*).$$

$$(4.1)$$

**Theorem 4.1.** Under the above setting, there is a sequence of sampling functions  $\{T_n(t)\}$  in T(G) such that for any  $x \in G$ 

$$f_x(t) = \sum_n \tilde{f}_x(t_n) T_n(t) \tag{4.2}$$

which converges in T(H) and uniformly on any subset of  $\Omega$  over which  $||k(t)||_H$  is bounded. Moreover, if  $\{x_n\}$  is a Riesz basis of H, then  $\{T_n(t)\}$  is a frame of T(G).

*Proof.* Applying T on both sides of (4.1) gives

$$f_x(t) = T(x)(t) = \sum_n \tilde{f}_x(t_n)T(P(x_n^*))(t)$$
$$= \sum_n \tilde{f}_x(t_n)T_n(t),$$

where  $T_n(t) = T(P(x_n^*))(t)$ . Since

$$\begin{aligned} |f_x(t) - \sum_{|n| \le N} \tilde{f}_x(t_n) T_n(t)| &= |T(x) - \sum_{|n| \le N} \tilde{f}_x(t_n) T(P(x_n^*))| \\ &= |\langle x - \sum_{|n| \le N} \tilde{f}_x(t_n) P(x_n^*), k(t) \rangle_H| \\ &\le ||x - \sum_{|n| \le N} \tilde{f}_x(t_n) P(x_n^*)||_H ||k(t)||_H \end{aligned}$$

the series (4.2) converges uniformly on any subset over which  $||k(t)||_H$  is bounded. Finally, if  $\{x_n\}$  is a Riesz basis of H, then  $\{x_n^*\}$  is also a Riesz basis of H so that  $\{P(x_n^*)\}$  is a frame of G since G is a closed subspace of H [1, Proposition 5.3.5]. Hence  $\{T_n(t) = T(P(x_n^*))(t)\}$  is a frame of T(G).

We may call (4.2) an oversampling expansion of  $f_x(t)$  for  $x \in G$ .

Now assume that finitely many sample values  $\{\tilde{f}_x(t_n) \mid n \in X = \{n_1, n_2, \cdots, n_N\}\}$ are missing. Applying  $\widetilde{T}$  on both sides of (4.1) gives

$$\tilde{f}_x(t) = \tilde{T}(x)(t) = \sum_n \tilde{f}_x(t_n)\tilde{T}(P(x_n^*))(t)$$
(4.3)

which converges not only in  $\widetilde{T}(H)$  but also pointwisely in  $\Omega$  since  $\widetilde{T}(H)$  is an RKHS. Setting  $t = t_{n_i}$  in (4.3), we have

$$\tilde{f}_{x}(t_{n_{j}}) = \sum_{n} \tilde{f}_{x}(t_{n}) \widetilde{T}(P(x_{n}^{*}))(t_{n_{j}}) \quad \text{for } 1 \le j \le N$$
$$= \sum_{k=1}^{N} \tilde{f}_{x}(t_{n_{k}}) \widetilde{T}(P(x_{n_{k}}^{*}))(t_{n_{j}}) + \sum_{n \notin X} \tilde{f}_{x}(t_{n}) \widetilde{T}(P(x_{n}^{*}))(t_{n_{j}}), \ 1 \le j \le N,$$

which can be rewritten in the matrix form as

$$(\mathbf{I} - \mathbf{T})\,\mathbf{f} = \mathbf{h}$$

where  $\mathbf{f} = (\tilde{f}_x(t_{n_1}), \cdots, \tilde{f}_x(t_{n_N}))^T$  is the column vector consisting of missing samples,  $\mathbf{h} = (h_1, \cdots, h_n)^T$ , where

$$h_j = \sum_{n \notin X} \tilde{f}(t_n) \widetilde{T}(P(x_n^*))(t_{n_j})$$

and  ${\bf T}$  is the  $N\times N$  matrix with entries

$$T_{ij} = \widetilde{T}(P(x_{n_j}^*))(t_{n_i}) = \langle P(x_{n_j}^*), x_{n_i} \rangle_H = \langle P(x_{n_j}^*), P(x_{n_i}) \rangle_H.$$

Note that if  $\mathbf{I} - \mathbf{T}$  is invertible, the missing samples  $\mathbf{f}$  can be recovered uniquely. In particular, if  $\langle \mathbf{Tv}, \mathbf{v} \rangle \neq ||\mathbf{v}||^2$  for any  $\mathbf{v} \in \mathbb{C}^N \setminus \{0\}$ , then  $\mathbf{I} - \mathbf{T}$  is invertible. We have:

**Theorem 4.2.** Under the same hypotheses as in Theorem 4.1, we assume further that  $\{x_n\}_n$  is a Riesz basis of H such that  $x_n = U(e_n)$  where  $\{e_n\}_n$  is an orthonormal basis of H and U is an automorphism of H. Then any finitely many missing samples  $\{\tilde{f}_x(t_{n_i}) \mid 1 \leq i \leq N\}$  in the oversampling expansion (4.2) can be uniquely recovered if PU = UP and

$$span\{e_{n_i} \mid 1 \le i \le N\} \cap G = \{0\}.$$
 (4.4)

*Proof.* Note first that  $x_n^* = (U^*)^{-1}(e_n)$  where  $\{x_n^*\}_n$  is the dual of  $\{x_n\}_n$ . Hence we have for any  $\mathbf{v} = (v_1, \cdots, v_N)^T \in \mathbb{C}^N \setminus \{0\},$ 

$$\begin{aligned} \langle \mathbf{T} \mathbf{v}, \mathbf{v} \rangle &= \sum_{i,j=1}^{N} \langle P(x_{n_j}^*), P(x_{n_i}) \rangle_H v_j \overline{v_i} \\ &= \langle P(U^*)^{-1} (\sum_{j=1}^{N} v_j e_{n_j}), PU(\sum_{i=1}^{N} v_i e_{n_i}) \rangle_H \\ &= \langle \sum_{j=1}^{N} v_j e_{n_j}, U^{-1} PU(\sum_{i=1}^{N} v_i e_{n_i}) \rangle_H \\ &= \langle \sum_{j=1}^{N} v_j e_{n_j}, P(\sum_{i=1}^{N} v_i e_{n_i}) \rangle_H \\ &= \| P(\sum_{j=1}^{N} v_j e_{n_j}) \|_H^2 \\ &< \| \sum_{j=1}^{N} v_j e_{n_j} \|_H^2 = \sum_{j=1}^{N} |v_j|^2 = \| \mathbf{v} \|^2 \end{aligned}$$

since  $\sum_{j=1}^{N} v_j e_{n_j} \notin G$  and  $\{e_n\}_n$  is an orthonormal basis of H. Hence  $\mathbf{I} - \mathbf{T}$  is invertible.

If moreover,  $\{x_n\}_n$  is an orthonormal basis of H in Theorem 4.2, then any finitely many missing samples  $\{\tilde{f}_x(t_{n_i}) \mid 1 \leq i \leq N\}$  can be uniquely recovered when the condition (4.4) holds.

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