# Supplementary Material: Controlling and Sampling Visibility Information on the Image Plane 

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## 1. Sampling Expansions for Arbitrary Sampling Locations

In the following, we summarize the central ideas required to construct sampling expansions for arbitrary sampling locations $\lambda_{k}$. We refer to [LDF14] for further details.

Let $\mathcal{H}(X)$ be a Hilbert-space, defined over a set $X$, where pointevaluation $\delta_{x}$ is a continuous functional. Then, by the Riesz representation theorem, there exists a function $k_{x} \in \mathcal{H}(X)$, possibly a different one for every $x \in X$, such that

$$
\begin{equation*}
\delta_{x}(f)=\left\langle k_{x}, f\right\rangle=f(x) \tag{1}
\end{equation*}
$$

where $\langle\cdot, \cdot\rangle$ denotes the inner product on $\mathcal{H}$. The function $k_{x}(y)$ is known as reproducing kernel.

To see the connection between sampling theorems and reproducing kernels, let $\left\{\lambda_{j}\right\}_{j \in \mathcal{N}}$ be a set of locations with $\lambda_{j} \in X$. Then, under suitable conditions on the distribution of the $\lambda_{j}$, the induced set $\left\{k_{\lambda_{j}}\right\}_{j \in \mathcal{N}}$ will be a frame, that is an in general redundant basis for $\mathcal{H}$. This implies the existence of dual functions $\tilde{k}_{j}(y)$ such that any $f \in \mathcal{H}$ can be written as

$$
\begin{equation*}
f(x)=\sum_{j \in \mathcal{N}}\left\langle f(y), \tilde{k}_{j}(y)\right\rangle k_{j}(x)=\sum_{j \in \mathcal{N}}\left\langle f(y), k_{j}(y)\right\rangle \tilde{k}_{j}(x) \tag{2}
\end{equation*}
$$

where the second equality follows by duality and we abbreviated $k_{j}(x) \equiv k_{\lambda_{j}}(x)$. Using the reproducing property in Eq. 1, we can write the last equation as

$$
\begin{equation*}
f(x)=\sum_{j \in \mathcal{N}} f\left(\lambda_{j}\right) \tilde{k}_{j}(x) \tag{3}
\end{equation*}
$$

Eq. 3 is the general form of a sampling expansion or theorem. The classical Shannon theorem is a special case where $\mathcal{H}(X)$ is the space of Fourier-bandlimited functions over $\mathbb{R}^{n}$, the $\lambda_{n}$ are formed by a dilated integer grid and $\tilde{k}_{n}(x)=k_{n}(x)=\operatorname{sinc}(x-n)$.

One can work numerically with the above construction using the series representation of $k_{x}(y)$ in an orthonormal basis $\left\{\phi_{i}\right\}$ for $\mathcal{H}$ :

$$
\begin{equation*}
k_{x}(y)=k_{y}(x)=\sum_{i} \phi_{i}(x) \phi_{i}(y) \tag{4}
\end{equation*}
$$

Assuming $\left\{\phi_{i}\right\}$ is $M$-dimensional with $M<\infty$, or has been truncated appropriately, and the same is true for $\left\{\lambda_{j}\right\}_{j \in \mathcal{N}}$, i.e $|\mathcal{N}|=$ $N<\infty$, then the basis representation of the set $\left\{k_{\lambda_{j}}\right\}$ in $\left\{\phi_{i}\right\}$ can
be written in matrix form

$$
K_{\phi}=\left(\begin{array}{ccc}
\phi_{1}\left(\lambda_{1}\right) & \cdots & \phi_{M}\left(\lambda_{1}\right)  \tag{5}\\
\vdots & \ddots & \vdots \\
\phi_{1}\left(\lambda_{N}\right) & \cdots & \phi_{m}\left(\lambda_{N}\right)
\end{array}\right) \in \mathbb{R}^{N \times M}
$$

This provides the change of basis matrix from $\left\{\phi_{i}\right\}$ to the reproducing kernel basis formed by the $k_{j}(x)$. In fact, it is easy to see that multiplying a signal's basis representations $\left(f_{1}, \cdots, f_{M}\right)$ in $\left\{\phi_{n}\right\}$ with $K_{\phi}$ yields the pointwise values $f\left(\lambda_{j}\right)$ that form the basis function coefficients in the expansion in Eq. 3. It is also not hard to see that when $\mathcal{H}(X)$ is the space of polynomials in the monomial basis over $\mathbb{R}$ then $K_{\phi}$ is the classical Vandermonde matrix.

It can be shown that the basis function coefficients of the dual kernel functions $\tilde{k}_{j}$ with respect to $\left\{\phi_{i}\right\}$ are given by the column of the sampling matrix $S_{\phi}=K_{\phi}^{-1}$. Since the construction of $K_{\phi}$ only requires the evaluation of the basis functions $\phi_{i}$ at the sampling locations $\lambda_{j}$ this provides a practical means to construct the sampling theorem in Eq. 3.

## 2. Convolution of $H(x)$ and Raised Cosine

The raised cosine function $\mathrm{Cr}_{B, \beta}$ is defined in the frequency domain as
$\hat{\operatorname{Cr}}(\xi)=\left\{\begin{array}{cc}1 & |\xi|<B \tilde{\beta}_{-} \\ \frac{1}{2}\left(1+\cos \left(\frac{\pi}{2 B \beta}(|\xi|-B(1-\beta))\right)\right) & B \tilde{\beta}_{-} \leq|\xi| \leq B \tilde{\beta}_{+} \\ 0 & \text { otherwise }\end{array}\right.$
with $\tilde{\beta}_{-}=1-\beta$ and $\tilde{\beta}_{+}=1+\beta$. It has the spatial representation

$$
\mathrm{Cr}_{B, \beta}(x)=\left\{\begin{array}{cl}
\frac{\pi B}{2} \operatorname{sinc}\left(\frac{1}{2 \beta}\right) & x= \pm \frac{1}{4 B \beta} \\
2 B \operatorname{sinc}(2 B x) \frac{\cos (2 \pi B \beta x)}{1-(4 B \beta x)^{2}} & \text { otherwise }
\end{array}\right.
$$

For $\beta=1 / n$ the convolution of $H(x)$ and the raised cosine func-
tion $\operatorname{Cr} B, \beta(x)$ is for $n=3,5,7, \cdots$ given by

$$
\begin{aligned}
& \operatorname{SCr}(x)=\frac{1}{8 \pi^{2}}\left(2 \pi+(-1)^{\frac{1-\beta}{2 \beta}}\left(\operatorname{Si}\left(\frac{\pi}{2} \frac{\beta_{-} \bar{\beta}_{+}}{\beta T}\right)+\operatorname{Si}\left(\frac{\pi}{2} \frac{\beta_{+} \bar{\beta}_{+}}{\beta T}\right)\right.\right. \\
&\left.+\operatorname{Si}\left(-\frac{\pi}{2} \frac{\beta_{-} \bar{\beta}_{-}}{\beta T}\right)+\operatorname{Si}\left(-\frac{\pi}{2} \frac{\beta_{+} \bar{\beta}_{-}}{\beta T}\right)\right) \\
&\left.-2 \operatorname{Si}\left(\frac{\pi \beta_{-} x}{T}\right)+2 \operatorname{Si}\left(\frac{\pi \beta_{+} x}{T}\right)\right)
\end{aligned}
$$

and for $n=2,4, \cdots$ by

$$
\begin{aligned}
& \operatorname{SCr}(x)=\frac{1}{8 \pi^{2}}\left(2 \pi+(-1)^{\frac{1}{2 \beta}}\left(-\operatorname{Ci}\left(\frac{\pi}{2} \frac{\beta_{-} \bar{\beta}_{+}}{\beta T}\right)+\operatorname{Ci}\left(\frac{\pi}{2} \frac{\beta_{+} \bar{\beta}_{+}}{\beta T}\right)\right.\right. \\
&\left.+\operatorname{Ci}\left(-\frac{\pi}{2} \frac{\beta_{-} \bar{\beta}_{-}}{\beta T}\right)-\operatorname{Ci}\left(-\frac{\pi}{2} \frac{\beta_{+} \bar{\beta}_{-}}{\beta T}\right)\right) \\
&\left.-2 \operatorname{Si}\left(\frac{\pi \beta_{-} x}{T}\right)+2 \operatorname{Si}\left(\frac{\pi \beta_{+} x}{T}\right)\right)
\end{aligned}
$$

where $\mathrm{Ci}(x)$ is the cosine-integral. Furthermore

$$
\begin{aligned}
& \beta_{-}=\beta-1 \\
& \beta_{+}=\beta+1 \\
& \bar{\beta}_{-}=-2 \beta x+T \\
& \bar{\beta}_{+}=2 \beta x+T .
\end{aligned}
$$

## References

[LDF14] Lessig C., Desbrun M., Fiume E.: A Constructive Theory of Sampling for Image Synthesis Using Reproducing Kernel Bases. ACM Transactions on Graphics (Proceedings of SIGGRAPH 2014) 33, 4 (jul 2014), 1-14. 1

