## Research Article

# Representing Smoothed Spectrum Estimate with the Cauchy Integral 

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Estimating power spectrum density (PSD) is essential in signal processing. This short paper gives a theorem to represent a smoothed PSD estimate with the Cauchy integral. It may be used for the approximation of the smoothed PSD estimate.

## 1. Introduction

Estimating power spectrum density (PSD) of signals plays a role in signal processing. It has applications to many issues in engineering [1-21]. Examples include those in biomedical signal processing, see, for example, $[1-3,6,12,13]$. Smoothing an estimate of PSD is commonly utilized for the purpose of reducing the estimate variance, see, for example, [22-29]. By smoothing a PSD estimate, one means that a smoothed estimate of PSD of a signal is the PSD estimate convoluted by a smoother function [30,31]. This short paper aims at providing a representation of a smoothed PSD estimate based on the Cauchy's integral.

## 2. Cauchy Representation of Smoothed PSD Estimate

Let $x(t)$ be a signal for $-\infty<t<\infty$. Let $S_{x x}(\omega)$ be its PSD, where $\omega=2 \pi f$ is radian frequency and $f$ is frequency. Then, by using the Fourier transform, $S_{x x}(\omega)$ is computed by

$$
\begin{equation*}
S_{x x}(\omega)=\left|\int_{-\infty}^{\infty} x(t) e^{-j \omega t} d t\right|^{2}, \quad j=\sqrt{-1} \tag{2.1}
\end{equation*}
$$

In practical terms, if $x(t)$ is a random signal, $S_{x x}(\omega)$ may never be achieved exactly because a PSD is digitally computed only in a finite interval, say, $\left(T_{1}, T_{2}\right)$ for $T_{1} \neq T_{2}$. Therefore, one can only attain an estimate of $S_{x x}(\omega)$.

Denote by $\widehat{S}_{x x}(\omega)$ an estimate of $S_{x x}(\omega)$. Then,

$$
\begin{equation*}
\widehat{S}_{x x}(\omega)=\left|\int_{T_{1}}^{T_{2}} x(t) e^{-j \omega t} d t\right|^{2} \tag{2.2}
\end{equation*}
$$

Without generality losing, we assume $T_{1}=0$ and $T_{2}=T$. Thus, the above becomes

$$
\begin{equation*}
\widehat{S}_{x x}(\omega)=\left|\int_{0}^{T} x(t) e^{-j \omega t} d t\right|^{2} \tag{2.3}
\end{equation*}
$$

In the discrete case, one has the following for a discrete signal $x(n)$ [21-23]:

$$
\begin{equation*}
\widehat{S}_{x x}(\omega)=\left|\sum_{n=0}^{N-1} x(n) e^{-j \omega n}\right|^{2} \tag{2.4}
\end{equation*}
$$

Because

$$
\begin{equation*}
\left|\sum_{n=L}^{N+L-1} x(n) e^{-j \omega n}\right|^{2} \neq\left|\sum_{n=M}^{N+M-1} x(n) e^{-j \omega n}\right|^{2} \quad \text { for } L \neq M \tag{2.5}
\end{equation*}
$$

$\widehat{S}_{x x}(\omega)$ is usually a random variable. One way of reducing the variance of $\widehat{S}_{x x}(\omega)$ is to smooth $\widehat{S}_{x x}(\omega)$ by a smoother function denoted by $G(\omega)$. Denote by $\widetilde{S}_{x x}(\omega)$ the smoothed PSD estimate. Let * imply the operation of convolution. Then, $\widetilde{S}_{x x}(\omega)$ is given by

$$
\begin{equation*}
\widetilde{S}_{x x}(\omega)=\widehat{S}_{x x}(\omega) * G(\omega) \tag{2.6}
\end{equation*}
$$

Assume that $\tilde{S}_{x x}(\omega)$ is differentiable any time for $-\infty<\omega<\infty$. Then, by using the Taylor series at $\omega=\omega_{0}, \widehat{S}_{x x}(\omega)$ is expressed by

$$
\begin{equation*}
\widehat{S}_{x x}(\omega)=\sum_{l=0}^{\infty} \frac{\widehat{S}_{x x}^{(l)}\left(\omega_{0}\right)}{l!}\left(\omega-\omega_{0}\right)^{n} \tag{2.7}
\end{equation*}
$$

Therefore,

$$
\begin{equation*}
\widetilde{S}_{x x}(\omega)=\sum_{l=0}^{\infty} \frac{\widehat{S}_{x x}^{(l)}\left(\omega_{0}\right)}{l!}\left(\omega-\omega_{0}\right)^{n} * G(\omega) \tag{2.8}
\end{equation*}
$$

Let $\omega-\omega_{0}=\omega_{1}$. Then,

$$
\begin{equation*}
\left(\omega-\omega_{0}\right)^{n} * G(\omega)=\omega_{1}^{n} * G\left(\omega_{1}+\omega_{0}\right) \tag{2.9}
\end{equation*}
$$

Thus, we have a theorem to represent $\widetilde{S}_{x x}(\omega)$ based on the Cauchy integral.
Theorem 2.1. Suppose $\widehat{S}_{x x}(\omega)$ is differentiable any time at $\omega_{0}$. Then, the smoothed PSD, that is, $\widetilde{S}_{x x}(\omega)$, may be expressed by

$$
\begin{equation*}
\widetilde{S}_{x x}(\omega)=\sum_{l=0}^{\infty} \frac{\widehat{S}_{x x}^{(l)}\left(\omega_{0}\right)}{l!} \omega_{1}^{l} * G\left(\omega_{1}+\omega_{0}\right)=\sum_{l=0}^{\infty} \widehat{S}_{x x}^{(l)}\left(\omega_{0}\right) \int_{0}^{\omega_{1}} \frac{\left(\omega_{1}-\omega_{\tau}\right)^{l}}{l!} G\left(\omega_{\tau}+\omega_{0}\right) d \omega_{\tau} \tag{2.10}
\end{equation*}
$$

Proof. The Cauchy integral in terms of $G\left(\omega_{\tau}+\omega_{0}\right)$ is in the form

$$
\begin{equation*}
\int_{0}^{\omega_{1}} \frac{\left(\omega_{1}-\omega_{\tau}\right)^{l}}{l!} G\left(\omega_{\tau}+\omega_{0}\right) d \omega_{\tau}=\underbrace{\int_{0}^{\omega_{\tau}} d \omega_{\tau} \cdots \int_{0}^{\omega_{\tau}} G\left(\omega_{\tau}+\omega_{0}\right) d \omega_{\tau}}_{l+1} \tag{2.11}
\end{equation*}
$$

That may be taken as the convolution between $\omega_{1}^{l} / l!$ and $G\left(\omega_{1}+\omega_{0}\right)$. Thus,

$$
\begin{equation*}
\frac{\omega_{1}^{l}}{l!} * G\left(\omega_{1}+\omega_{0}\right)=\int_{0}^{\omega_{1}} \frac{\left(\omega_{1}-\omega_{\tau}\right)^{l}}{l!} G\left(\omega_{\tau}+\omega_{0}\right) d \omega_{\tau} \tag{2.12}
\end{equation*}
$$

Therefore, (2.10) holds. This completes the proof.
The present theorem is a theoretic representation of a smoothed PSD estimate. It may yet be a method to be used in the approximation of a smoothed PSD estimate. As a matter of fact, we may approximate $\widetilde{S}_{x x}(\omega)$ by a finite series given by

$$
\begin{equation*}
\widetilde{S}_{x x}(\omega) \approx \sum_{l=0}^{L} \widehat{S}_{x x}^{(l)}\left(\omega_{0}\right) \int_{0}^{\omega_{1}} \frac{\left(\omega_{1}-\omega_{\tau}\right)^{l}}{l!} G\left(\omega_{\tau}+\omega_{0}\right) d \omega_{\tau} . \tag{2.13}
\end{equation*}
$$

From the above theorem, we have the following corollary.
Corollary 2.2. Suppose $\widehat{S}_{x x}(\omega)$ is differentiable any time at $\omega=0$. Then, $\widetilde{S}_{x x}(\omega)$ may be expressed by

$$
\begin{equation*}
\widetilde{S}_{x x}(\omega)=\sum_{l=0}^{\infty} \frac{\widehat{S}_{x x}^{(l)}(0)}{l!} \omega^{l} * G(\omega)=\sum_{l=0}^{\infty} \widehat{S}_{x x}^{(l)}(0) \int_{0}^{\omega} \frac{\left(\omega-\omega_{\tau}\right)^{l}}{l!} G\left(\omega_{\tau}\right) d \omega_{\tau} \tag{2.14}
\end{equation*}
$$

The proof is omitted since it is straightforward when one takes into account the proof of theorem.

## 3. Conclusions

We have presented a theorem with respect to a representation of a smoothed PSD estimate of signals based on the Cauchy integral. The theorem constructively implies that the design of a smoother function $G(\omega)$ may consider the approximation described by the Cauchy integral with the finite Taylor series (2.13). In addition, the smoother function $G(\omega)$ can also be taken as a solution to the integral equation (2.14), which is worth being investigated in the future.

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