

Computational Physics – Lecture 18

(22 April 2020)

Recap

In the previous class, we acquired the capability of numerically computing the Fourier Transform of a function.

Recap

The FT of a function $f(x)$, given by

$$\tilde{f}(k) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} dx \cdot f(x) \cdot \exp(-ikx), \quad (1)$$

can be computed at $k_q = 2\pi q/n\Delta$, for $q = 0, \dots, n-1$, by choosing some x_{\min} , x_{\max} and Δ , and computing

$$\tilde{f}(k_q) = \Delta \cdot \sqrt{\frac{n}{2\pi}} \cdot \exp(-ik_q \cdot x_{\min}) \cdot \text{DFT}[\{f(x_p)\}], \quad (2)$$

where $x_p = x_{\min} + p\Delta$ for $p = 0, \dots, n-1$, the number n is given by

$$n = \frac{x_{\max} - x_{\min}}{\Delta} + 1, \quad (3)$$

and $\{f(x_p)\}$ is the set of numbers

$$\{f(x_p) \mid p = 0, \dots, n-1\}. \quad (4)$$

Recap

Excellent libraries for computing the FT are commercially available. For example, Numpy, GSL, and FFTW.

But before using these libraries we should always read their documentation and check

- ▶ The DFT formula used by the library, and
- ▶ The frequency ordering assumed by the library.

Today's plan

In today's class, we want to understand how to convolve two functions numerically.

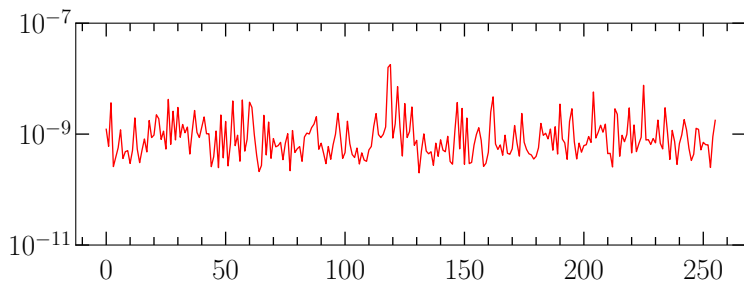
Convolution

The convolution of two functions $g(x)$ and $h(x)$ is defined as

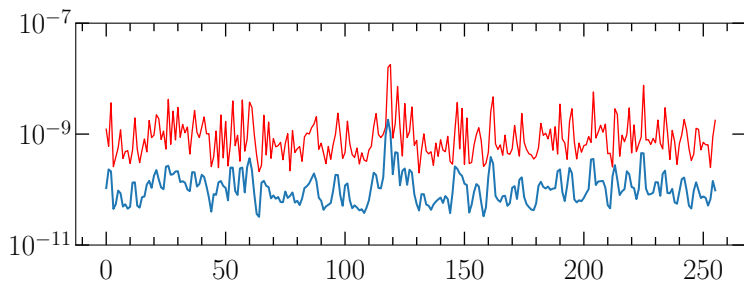
$$f(x) \equiv [g \otimes h](x) = \int_{-\infty}^{\infty} dr \cdot g(r) \cdot h(x - r). \quad (5)$$

This *smears* one function by another.

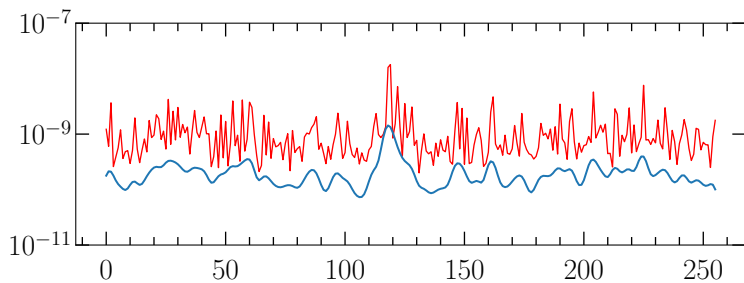
Convolution



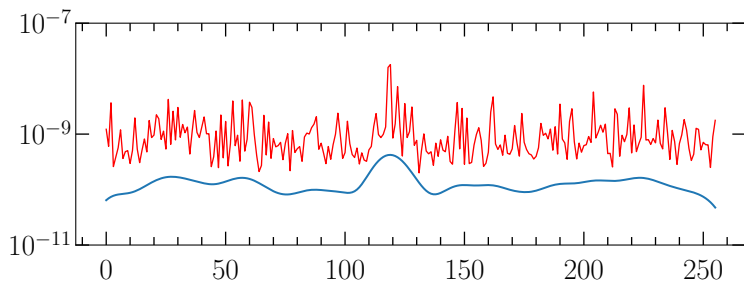
Convolution



Convolution



Convolution



Convolution Theorem

The *convolution theorem* says that

$$\tilde{f}(k) = \sqrt{2\pi} \cdot \tilde{g}(k) \cdot \tilde{h}(k). \quad (6)$$

The Fourier Transform of the convolution of two functions is equal to the product of the individual Fourier Transforms of the two functions.

Convolution Theorem

$$\begin{aligned}\tilde{f}(k) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} dx \cdot f(x) \cdot \exp(-ikx) \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} dx \cdot \left[\int_{-\infty}^{\infty} dr \cdot g(r) \cdot h(x-r) \right] \cdot \exp(-ikx)\end{aligned}$$

Change variable from x to $u = x - r$.

$$\begin{aligned}\tilde{f}(k) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} du \int_{-\infty}^{\infty} dr g(r) h(u) \exp(-ik[u+r]) \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} du \int_{-\infty}^{\infty} dr g(r) h(u) \exp(-iku) \exp(-ikr)\end{aligned}$$

Convolution Theorem

$$\begin{aligned}\tilde{f}(k) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} du \int_{-\infty}^{\infty} dr g(r) h(u) \exp(-iku) \exp(-ikr) \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} du h(u) \exp(-iku) \int_{-\infty}^{\infty} dr g(r) \exp(-ikr) \\ &= \tilde{h}(k) \cdot \sqrt{2\pi} \tilde{g}(k) \\ &= \sqrt{2\pi} \cdot \tilde{h}(k) \cdot \tilde{g}(k)\end{aligned}\tag{7}$$

Discrete convolution

To do convolution on computers, we have discretise the above relations by sampling all the functions.

Let g_p be a sample of $g(x)$ and h_p be a sample of $h(x)$, where $p = 0, \dots, n - 1$.

Then we can define the discrete convolution of these samples such that the convolution theorem holds for them.

In other words, we define the discrete convolution as

$$f_p = \sum_{r=0}^{n-1} g_r h_{p-r}. \quad (8)$$

Discrete convolution theorem

When the discrete convolution is defined this way, we have

$$\tilde{f}_q = \sqrt{n} \cdot \tilde{h}_q \cdot \tilde{g}_q. \quad (9)$$

It is easier to see this using the unscaled expressions:

$$\tilde{w}_q = \frac{1}{\sqrt{n}} \sum_{p=0}^{n-1} w_p \cdot \exp\left(\frac{-i2\pi qp}{n}\right), \quad (10)$$

and the inverse is

$$w_p = \frac{1}{\sqrt{n}} \sum_{q=0}^{n-1} \tilde{w}_q \cdot \exp\left(\frac{i2\pi qp}{n}\right). \quad (11)$$

Discrete convolution theorem

We have

$$\begin{aligned}\tilde{f}_q &= \frac{1}{\sqrt{n}} \sum_{p=0}^{n-1} f_p \cdot \exp\left(\frac{-i2\pi qp}{n}\right) \\&= \frac{1}{\sqrt{n}} \sum_{p=0}^{n-1} \sum_{r=0}^{n-1} g_r h_{p-r} \cdot \exp\left(\frac{-i2\pi qp}{n}\right) \\&= \frac{1}{\sqrt{n}} \sum_{p=0}^{n-1} \sum_{r=0}^{n-1} g_r h_{p-r} \cdot \exp\left(\frac{-i2\pi q[p-r]}{n}\right) \exp\left(\frac{-i2\pi qr}{n}\right) \\&= \frac{1}{\sqrt{n}} \sum_{u=0}^{n-1} h_u \exp\left(\frac{-i2\pi qu}{n}\right) \sum_{r=0}^{n-1} g_r \exp\left(\frac{-i2\pi qr}{n}\right) \\&= \sqrt{n} \cdot \tilde{h}_q \cdot \tilde{g}_q.\end{aligned}$$

(We have assumed that h is n -periodic.)

Consistency between DFT and FT

Is the above discrete convolution consistent with the continuous convolution?

Let us assume $x_{\min} = 0$ and write

$$\tilde{g}(k_q) = \Delta \cdot \sqrt{\frac{n}{2\pi}} \cdot \text{DFT} [\{g(x_p)\}], \quad (12)$$

and

$$\tilde{h}(k_q) = \Delta \cdot \sqrt{\frac{n}{2\pi}} \cdot \text{DFT} [\{h(x_p)\}]. \quad (13)$$

Consistency between DFT and FT

Now expect that the inverse DFT of

$$\sqrt{2\pi} \cdot \tilde{h}(k_q) \cdot \tilde{g}(k_q) \quad (14)$$

should be $f(x_p)$.

We have

$$\sqrt{2\pi} \cdot \tilde{h}(k_q) \cdot \tilde{g}(k_q) \quad (15)$$

$$= \sqrt{2\pi} \cdot \Delta^2 \cdot \frac{n}{2\pi} \cdot \text{DFT}[\{g(x_p)\}] \cdot \text{DFT}[\{h(x_p)\}] \quad (16)$$

What is the IDFT of this?

Consistency between DFT and FT

The IDFT is

$$\begin{aligned} & \frac{1}{\sqrt{n}} \sum_{q=0}^{n-1} \sqrt{2\pi} \cdot \Delta^2 \cdot \frac{n}{2\pi} \cdot \text{DFT} [\{g(x_p)\}]_q \cdot \text{DFT} [\{h(x_p)\}]_q \cdot \exp (ik_q x_p) \\ &= \Delta^2 \cdot \sqrt{\frac{n}{2\pi}} \cdot \sum_{q=0}^{n-1} \text{DFT} [\{g(x_p)\}]_q \cdot \text{DFT} [\{h(x_p)\}]_q \cdot \exp (ik_q x_p) \\ &= \Delta^2 \sqrt{\frac{n}{2\pi}} \sum_{q=0}^{n-1} \left\{ \left[\sum_{p'=0}^{n-1} \frac{g(x_{p'})}{\sqrt{n}} \exp (-ik_q x_{p'}) \right] \right. \\ & \quad \times \left. \left[\sum_{p''=0}^{n-1} \frac{h(x_{p''})}{\sqrt{n}} \exp (-ik_q x_{p''}) \right] \cdot \exp (ik_q x_p) \right\} \end{aligned}$$

Consistency between DFT and FT

$$\begin{aligned} &= \frac{\Delta^2}{\sqrt{2\pi n}} \sum_{q=0}^{n-1} \sum_{p'=0}^{n-1} \sum_{p''=0}^{n-1} g(x_{p'}) h(x_{p''}) \exp(-ik_q [x_{p'} + x_{p''} - x_p]) \\ &= \frac{\Delta^2}{\sqrt{2\pi n}} \cdot n \sum_{p'=0}^{n-1} \sum_{p''=0}^{n-1} g(x_{p'}) h(x_{p''}) \delta_{p,p'+p''} \\ &= \Delta^2 \sqrt{\frac{n}{2\pi}} \sum_{p'=0}^{n-1} \sum_{p''=0}^{n-1} g(x_{p'}) h(x_{p''}) \delta_{p,p'+p''} \\ &= \Delta^2 \sqrt{\frac{n}{2\pi}} \sum_{p'=0}^{n-1} g(x_{p'}) h(x_{p-p'}). \end{aligned}$$

Consistency between DFT and FT

Or, to simplify the argument a bit, the IDFT of

$$\text{DFT} [\{g(x_p)\}] \cdot \text{DFT} [\{h(x_p)\}] \quad (17)$$

is

$$\frac{\Delta^2 \sqrt{\frac{n}{2\pi}} \sum_{p'=0}^{n-1} g(x_{p'}) h(x_{p-p'})}{\sqrt{2\pi} \cdot \Delta^2 \cdot \frac{n}{2\pi}} \quad (18)$$

which is just

$$\frac{1}{\sqrt{n}} \sum_{p'=0}^{n-1} g(x_{p'}) h(x_{p-p'}). \quad (19)$$

Is this related to $f(x_p)$?

Consistency between DFT and FT

Recall

$$f(x_p) = \int_{-\infty}^{\infty} dr \cdot g(r) \cdot h(x_p - r). \quad (20)$$

If we discretise this, we get

$$f(x_p) = \sum_{p'=0}^{n-1} g(x_{p'}) h(x_{p-p'}) \quad (21)$$

$$= \Delta \cdot \sum_{p'=0}^{n-1} g(x_{p'}) h(x_{p-p'}) \quad (22)$$

$$= \Delta \cdot \sqrt{n} \cdot \text{IDFT} \left(\text{DFT} [\{g(x_p)\}] \cdot \text{DFT} [\{h(x_p)\}] \right) \quad (23)$$

Consistency between DFT and FT

So our definitions of continuous and discrete convolution are consistent.

To compute the convolution of two functions,

- ▶ Sample them and take their discrete Fourier transforms
- ▶ Multiply the Fourier transforms
- ▶ Take the inverse discrete Fourier transform of the result
- ▶ Multiply the result by $\Delta \cdot \sqrt{n}$

Example

Let us consider the two functions

$$g(x) = \exp(-x^2) \quad (24)$$

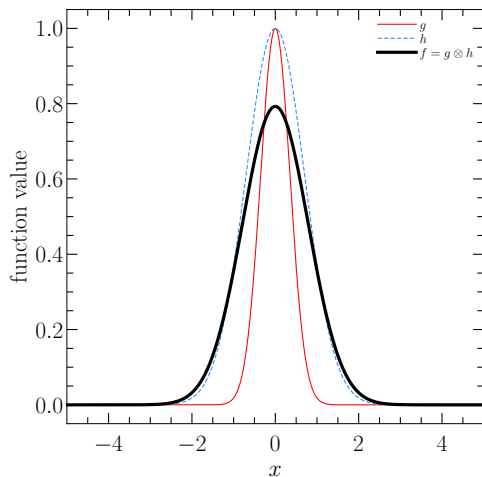
and

$$h(x) = \exp(-4x^2). \quad (25)$$

The convolution of these two functions can be calculated analytically, and is given by

$$f(x) = \sqrt{\frac{\pi}{5}} \exp\left(\frac{-4x^2}{5}\right) \quad (26)$$

Example



(Convolution of two Gaussians is a Gaussian.)

Example

We can calculate the Fourier transforms of $f(x)$, $g(x)$, and $h(x)$ analytically and confirm the convolution theorem.

We have

$$\tilde{g}(k) = \frac{1}{\sqrt{2}} \exp\left(\frac{-k^2}{4}\right), \quad (27)$$

and

$$\tilde{h}(k) = \frac{1}{2\sqrt{2}} \exp\left(\frac{-k^2}{16}\right), \quad (28)$$

and

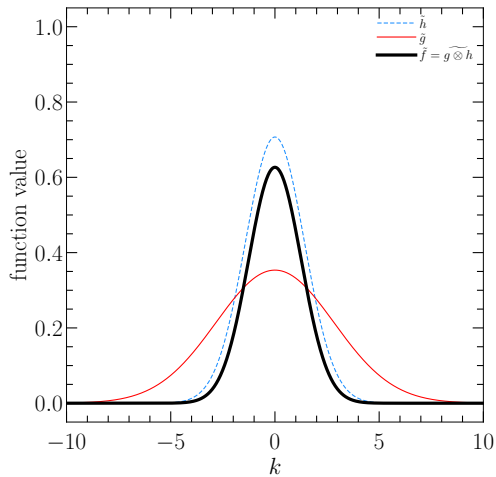
$$\tilde{f}(k) = \frac{1}{2} \sqrt{\frac{\pi}{2}} \exp\left(\frac{-5k^2}{16}\right). \quad (29)$$

Example

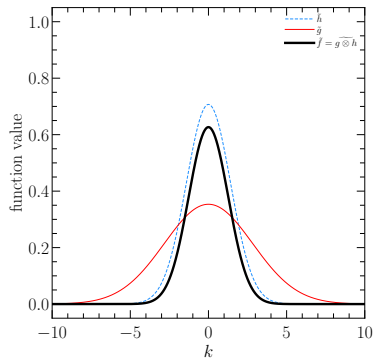
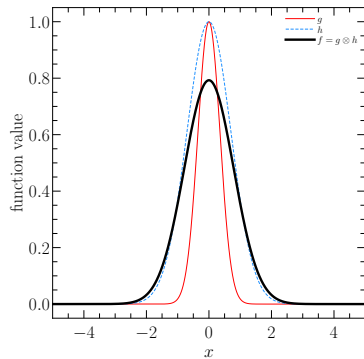
So the convolution theorem holds.

$$\begin{aligned} & \sqrt{2\pi} \cdot \tilde{g}(k) \cdot \tilde{h}(k) \\ &= \sqrt{2\pi} \cdot \left[\frac{1}{\sqrt{2}} \exp\left(\frac{-k^2}{4}\right) \right] \cdot \left[\frac{1}{2\sqrt{2}} \exp\left(\frac{-k^2}{16}\right) \right] \\ &= \frac{1}{2} \sqrt{\frac{\pi}{2}} \exp\left(\frac{-5k^2}{16}\right) \\ &= \tilde{f}(k). \end{aligned}$$

Example

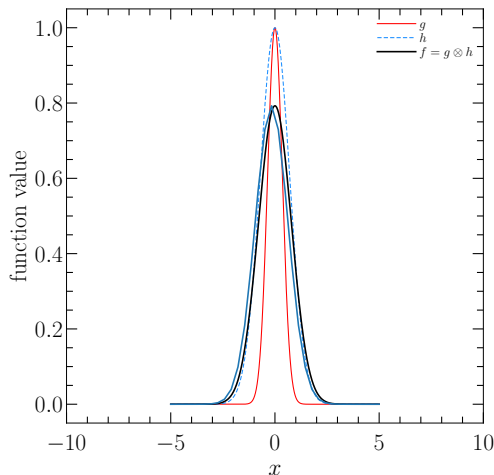


Example



Example

However, when we compute the convolution using our new method we find



(I used $x_{\min} = -5$, $x_{\max} = 5$, and $n = 32$.)

Zero padding

The result is not accurate because the discrete convolution assumes that our function $h(x_p)$ is periodic, but it is not.

We can avoid this problem by means of zero padding.

Consider the simple case of $n = 4$, in which we have

$$f_p = \sum_{r=0}^3 g_r h_{p-r}. \quad (30)$$

Zero padding

We expect

$$f_0 = g_0h_0 + g_1h_{-1} + g_2h_{-2} + g_3h_{-3} \quad (31)$$

$$= g_0h_0, \quad (32)$$

but due to periodicity we get

$$f_0 = g_0h_0 + g_1h_{-1} + g_2h_{-2} + g_3h_{-3} \quad (33)$$

$$= g_0h_0 + g_1h_3 + g_2h_2 + g_3h_1, \quad (34)$$

which is wrong.

Zero padding

Now suppose we expand our $n = 4$ array to an $n = 8$ array for which the last four elements are zero.

Now we will have

$$f_p = \sum_{r=0}^7 g_r h_{p-r}. \quad (35)$$

which will give us

$$\begin{aligned} f_0 &= g_0 h_0 + g_1 h_{-1} + g_2 h_{-2} + g_3 h_{-3} + g_4 h_{-4} \\ &\quad + g_5 h_{-5} + g_6 h_{-6} + g_7 h_{-7} \end{aligned} \quad (36)$$

$$= g_0 h_0 + g_1 h_{-1} + g_2 h_{-2} + g_3 h_{-3} \quad (37)$$

$$= g_0 h_0 + g_1 h_7 + g_2 h_6 + g_3 h_5 \quad (38)$$

$$= g_0 h_0, \quad (39)$$

which is now the correct answer.

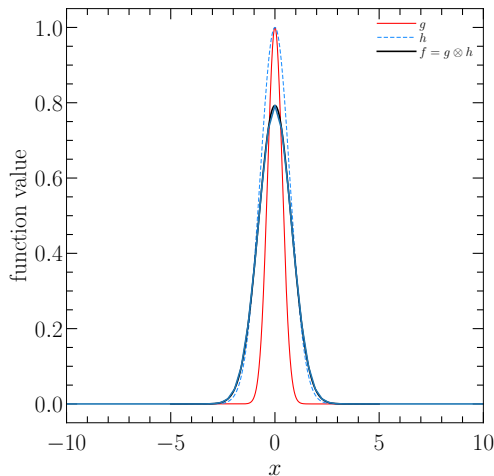
Zero padding

With zero padding, to compute the convolution of two functions we do the following:

- ▶ Sample the functions *and zero pad them*
- ▶ Take their discrete Fourier transforms
- ▶ Multiply the Fourier transforms
- ▶ Take the inverse discrete Fourier transform of the result
- ▶ Multiply the result by $\Delta \cdot \sqrt{n}$

Example

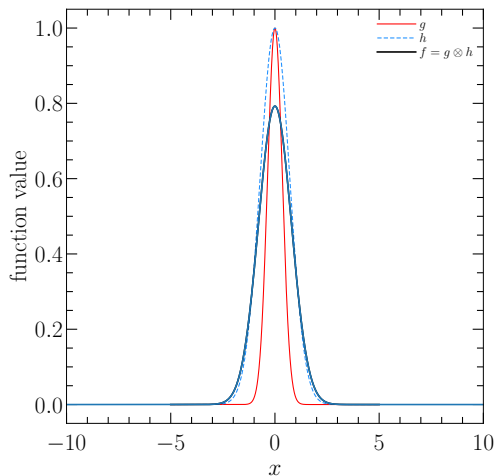
With zero padding in our example, we get



($x_{\min} = -5$, $x_{\max} = 5$, and $n = 32$.)

Example

We can increase the resolution for a better result:



($x_{\min} = -5$, $x_{\max} = 5$, and $n = 1024$.)

Deconvolution

We now know how to numerically compute the convolution $g \otimes h$ of two functions g and h .

But if we are given $g \otimes h$ and g , we can then also compute h by simply dividing the Fourier transforms.

This is called deconvolution.

We can think of this as “removing instrumental response”.

Optimal filtering

Suppose we want to measure an uncorrupted signal $u(t)$ but an experiment as produced a corrupted signal $c(t)$, given by

$$c(t) = s(t) + n(t) \quad (40)$$

where

$$s(t) = \int_{-\infty}^{\infty} r(t - \tau) \cdot u(\tau) d\tau \quad (41)$$

If there was not noise, we can solve this problem by deconvolution.

Optimal filtering

In presence of noise, we try to find the *optimal filter* $\phi(t)$ such that when this is applied to $c(t)$, and the result is deconvolved by $r(t)$, we get something, say $u'(t)$, that is as close as possible to $u(t)$.

So we will calculate

$$\tilde{u}'(k) = \frac{\tilde{c}(k)\tilde{\phi}(k)}{\tilde{r}(k)} \quad (42)$$

and solve this for ϕ such that

$$\int_{-\infty}^{\infty} |u'(t) - u(t)|^2 dt$$

is minimised.

Optimal filtering

But this is equal to the condition that

$$\int_{-\infty}^{\infty} |\tilde{u}'(k) - \tilde{u}(k)|^2 dk$$

is minimised.

Or

$$\begin{aligned} & \int_{-\infty}^{\infty} \left| \frac{[\tilde{s}(k) + \tilde{n}(k)] \tilde{\phi}'(k)}{\tilde{r}'(k)} - \frac{\tilde{s}(k)}{\tilde{r}(k)} \right|^2 dk \\ &= \int_{-\infty}^{\infty} |\tilde{r}(k)|^{-2} \left\{ |\tilde{s}(k)|^2 |1 - \tilde{\phi}(k)|^2 + |\tilde{n}(k)|^2 |\tilde{\phi}(k)|^2 \right\} dk \end{aligned}$$

is minimised. (Cross terms integrate to zero.)

Optimal filtering

Differentiating by ϕ and setting the result to zero gives

$$\tilde{\phi}(k) = \frac{|\tilde{s}(k)|^2}{|\tilde{s}(k)|^2 + |\tilde{n}(k)|^2}. \quad (43)$$

This is called the Optimal Filter, or the Wiener Filter.

It requires us to know $|\tilde{s}(k)|^2$ and $|\tilde{n}(k)|^2$.

You can make this process more sophisticated by using better optimisation ideas.