

CS 216 Homework 2

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Problem 1

We will prove that $(f * g) * h = f * (g * h)$. First off, let $x = f * g$ and let $y = g * h$.

$$x(t) = (f * g)(t) = \sum_{s=-\infty}^{\infty} f(t-s)g(s)$$

$$y(t) = (g * h)(t) = \sum_{s=-\infty}^{\infty} g(s)h(t-s)$$

This means that

$$(x * h)(t) = \sum_{v=-\infty}^{\infty} x(v)h(t-v) = \sum_{v=-\infty}^{\infty} \sum_{s=-\infty}^{\infty} f(v-s)g(s)h(t-v)$$

Similarly

$$(f * y)(t) = \sum_{v=-\infty}^{\infty} f(t-v)y(v) = \sum_{v=-\infty}^{\infty} \sum_{s=-\infty}^{\infty} f(t-v)g(s)h(v-s)$$

In the second equation, do a change of variables $v = t - v' + s$ which does not change the final result since we are going from negative infinity to infinity. For the second equation, we end up with

$$(f * y)(t) = \sum_{v'=-\infty}^{\infty} \sum_{s=-\infty}^{\infty} f(v'-s)g(s)h(t-v')$$

As can be observed, the first and second equation are now equal. This proves that $(x * h)(t) = (f * y)(t)$ and since this applies for any three functions, we have proven that convolution is associative.

Problem 2

If we correlate a function f with an impulse function, we get $f(-t)$, so the function gets flipped around the y-axis.

Here is the proof:

Take the impulse function g , so $g(0) = 1$ and $g(x) = 0$ for all other x

Let $*$ be the correlation operation in this case.

$$(f * g)(t) = \sum_{s=-\infty}^{\infty} f(s)g(s+t)$$

In our case, the inner term is always 0 except for when $s+t=0$ so $s=-t$, thus $(f * g)(t) = f(-t)$, proving our assertion.

Now let $h(t) = g(t)$. We will prove that $(f * g) * h \neq f * (g * h)$.

For the right hand side, by what was shown above,

$g * h = g$ since the impulse function is symmetric around the y-axis.

This means that $(f * (g * h))(t) = (f * g)(t) = f(-t)$.

For the left hand side, by what was shown above,

$(f * g)(t) = f(-t)$ thus $((f * g) * h)(t) = (f(-t)) * h(t)$

This will flip the function back to its original position, thus the left hand side is equal to $f(t)$

For any non-symmetric function f , such as $f(t) = 3t + 5$, it holds that $f(t) \neq f(-t)$

thus the left hand side is not equal to the right hand side.

Since we have example functions whose correlations are not associative, there is no way correlation is associative.

Problem 3

Let $g_1(x) = g_2(y) = N(0, \sigma^2)$. Then

$$g_1(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

$$g_2(y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{y^2}{2\sigma^2}}$$

This means that

$$g_1(x)g_2(y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

This is equal to $g(x, y)$, thus allowing us to say that $g(x, y) = g_1(x)g_2(y)$

Problem 4

For the spatial domain running time, we can think of convolution as the following:

- For each pixel in the image, we apply the filter to it.

Thus there are $H \cdot W$ iterations of the filter

Each filter will take $M \cdot N$ time.

Thus the time complexity is $O(MNHW)$

If we use FFT, this would be the procedure:

1. Convert the signal to frequency
2. Convert the filter to frequency
3. Do element wise multiplication of the two new vectors.
4. Convert the elements back.

Step 1 will take $MN \cdot \log(MN)$ time

Step 2 will take $HW \cdot \log(HW)$ time

Step 3 will take $\max(HW, MN)$ time. The identity of the max will not matter in the end since the previous step eclipses this one.

Step 4 will take $\max(HW, MN) \log(\max(HW, MN))$ time. Again which one is the max does not matter because of step 1 and 2.

The total running time is thus $O(MN \cdot \log(MN) + HW \cdot \log(HW))$ in the case where we use FFT.

Assuming that HW is the max, the running time is $O(HW \cdot \log(HW))$.

If the filter is $f(x, y) = f_1(x)f_2(y)$, let F be the Fourier transform, then the following happens by properties of convolution and the Fourier transform

$$F(I * f) = F(I) \cdot F(f) = F(I) \cdot (F(f_1) * F(f_2))$$

Thus the procedure would be the following:

1. Compute FFT of horizontal filter
2. Compute FFT of the vertical filter
3. Do convolution of the two FFTs found
4. Compute FFT of the image
5. Do point-wise multiplication of the FFT of the image with the filter found in step 3.

Step 1 and 2 will take $M \log(M) + N \log(N)$ time.

If we do step 3 using the above convolution procedure, then it takes $M \log(M)$ time.

Step 4 will take $HW \log(HW)$ time.

Assuming HW dominates, step 5 will take HW time.

Assuming that HW is greater than M or N , step 4 and 5 dominate.

The total running time is thus $O(HW \log(HW))$ time.

TODO: Check this

Problem 5

Our two gaussians are as follows

$$g_1(t) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{t^2}{2\sigma_1^2}}$$

$$g_2(t) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{t^2}{2\sigma_2^2}}$$

The convolution formula we will use is the following

$$g_3(t) = \int_{-\infty}^{\infty} g_1(s)g_2(t-s) ds$$

Let F_1 be the Fourier transform for g_1 and F_2 be the transform for g_2 .

$$F_1(t) = \int_{-\infty}^{\infty} g_1(s)e^{-2\pi ist} ds$$

$$F_2(t) = \int_{-\infty}^{\infty} g_2(s)e^{-2\pi ist} ds$$

Expanding we have

$$F_1(t) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \int_{-\infty}^{\infty} e^{-\frac{s^2}{2\sigma_1^2}} e^{-2\pi ist} ds$$

$$F_2(t) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \int_{-\infty}^{\infty} e^{-\frac{s^2}{2\sigma_2^2}} e^{-2\pi ist} ds$$

Expanding the imaginery exponent

$$F_1(t) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \int_{-\infty}^{\infty} e^{-\frac{s^2}{2\sigma_1^2}} (\cos(2\pi st) + i\sin(2\pi st)) ds$$

$$F_2(t) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \int_{-\infty}^{\infty} e^{-\frac{s^2}{2\sigma_2^2}} (\cos(2\pi st) + i\sin(2\pi st)) ds$$

Since the sine is an odd function, the integral of it will go to zero, thus we can simplify the above equations

$$F_1(t) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \int_{-\infty}^{\infty} e^{-\frac{s^2}{2\sigma_1^2}} \cos(2\pi st) ds$$

$$F_2(t) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \int_{-\infty}^{\infty} e^{-\frac{s^2}{2\sigma_2^2}} \cos(2\pi st) ds$$

By what was asserted in Wolfram Alpha, on this web page:

<http://mathworld.wolfram.com/FourierTransformGaussian.html>

$$F_1(t) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \sqrt{2\pi\sigma_1^2} e^{-2\pi^2 t^2 \sigma_1^2}$$

$$F_2(t) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \sqrt{2\pi\sigma_2^2} e^{-2\pi^2 t^2 \sigma_2^2}$$

Simplifying we have the following

$$F_1(t) = e^{-2\pi^2 t^2 \sigma_1^2}$$

$$F_2(t) = e^{-2\pi^2 t^2 \sigma_2^2}$$

Let $F = F_1 \cdot F_2$ then we have

$$F(t) = e^{-2\pi^2 t^2 (\sigma_1^2 + \sigma_2^2)}$$

Let $\sigma = -2\pi^2(\sigma_1^2 + \sigma_2^2)$, then

$$F(t) = e^{\sigma t^2}$$

We want the inverse transform of that function to get the finished function.

$$g_3(x) = \int_{-\infty}^{\infty} e^{2\pi i x t} F(t) dt$$

$$g_3(x) = \int_{-\infty}^{\infty} e^{2\pi i x t} e^{\sigma t^2} dt$$

From what we did before (TODO: Add in more detail)

$$g_3(x) = \int_{-\infty}^{\infty} \cos(2\pi x t) e^{\sigma t^2} dt$$

By the same logic used above, we can say that

$$g_3(x) = \sqrt{-\frac{\pi}{\sigma}} e^{\frac{\pi^2 x^2}{\sigma}}$$

Expanding σ and then simplifying, we have

$$g_3(x) = \sqrt{\frac{1}{2\pi(\sigma_1^2 + \sigma_2^2)}} e^{-\frac{x^2}{2(\sigma_1^2 + \sigma_2^2)}}$$

If we let $\sigma_3 = \sqrt{\sigma_1^2 + \sigma_2^2}$ then we have

$$g_3(x) = \sqrt{\frac{1}{2\pi\sigma_3^2}} e^{-\frac{x^2}{2\sigma_3^2}}$$

This is clearly a Gaussian, thus we have proved that g_3 is a Gaussian with the variance of σ_3 as defined above.

Problem 6

Here are the initial plots

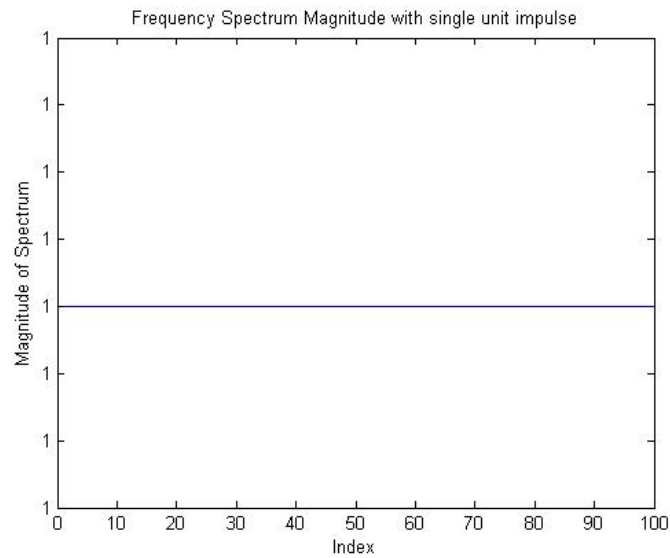


Figure 1: Frequency Spectrum Magnitude Plot for single impulse

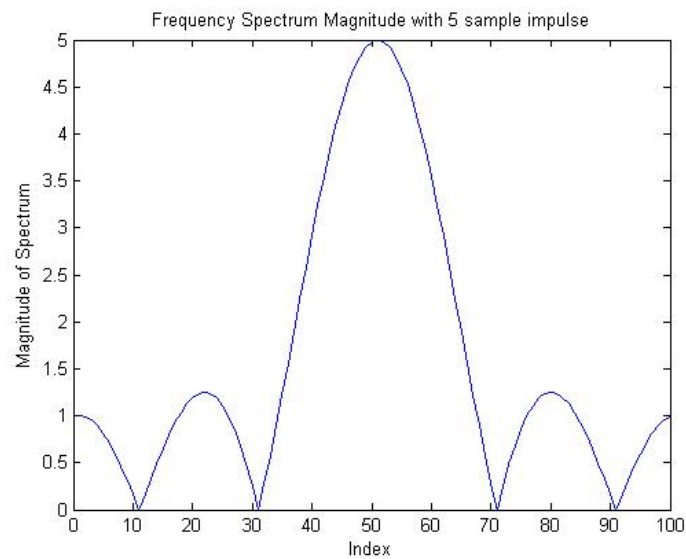


Figure 2: Frequency Spectrum Magnitude Plot for 5 sample impulse

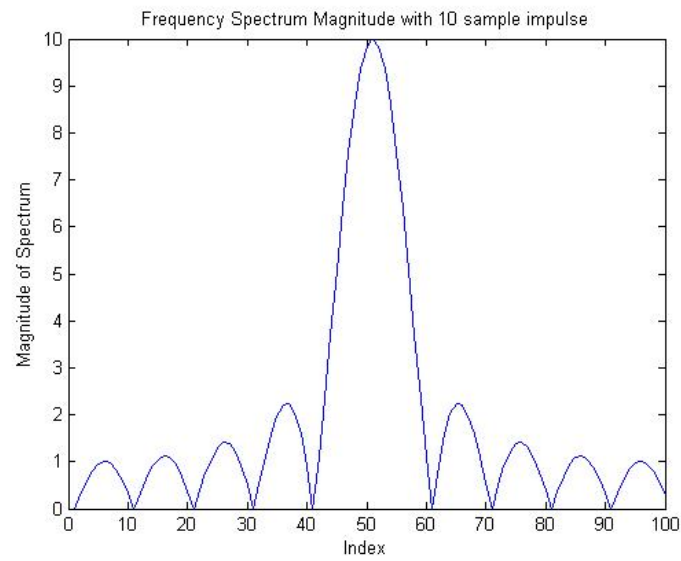
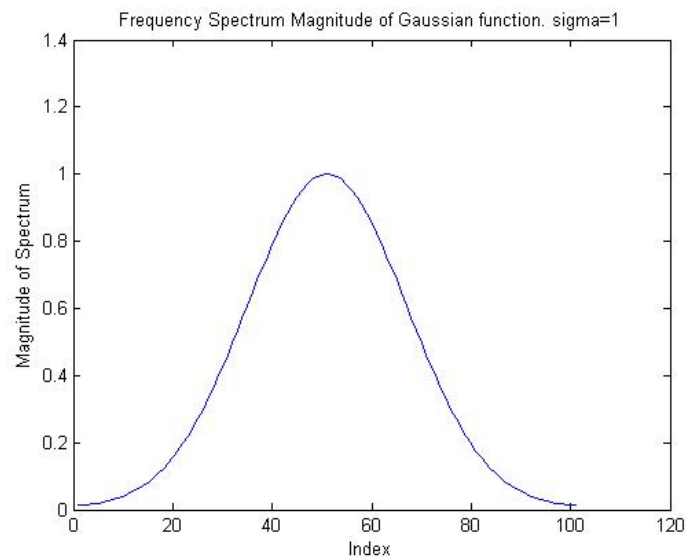


Figure 3: Frequency Spectrum Magnitude Plot for 10 sample impulse

Figure 4: Frequency Spectrum Magnitude Plot for Gaussian Function with $\sigma = 1$

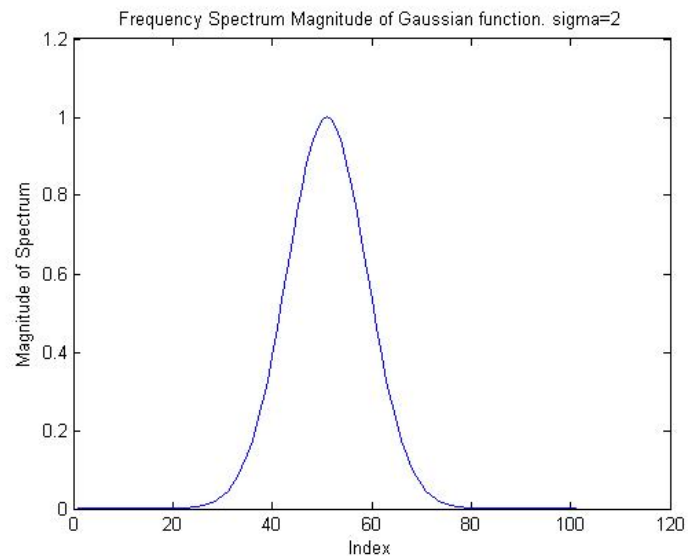


Figure 5: Frequency Spectrum Magnitude Plot for Gaussian Function with $\sigma = 2$

Here is the magnitude, phase experiment results

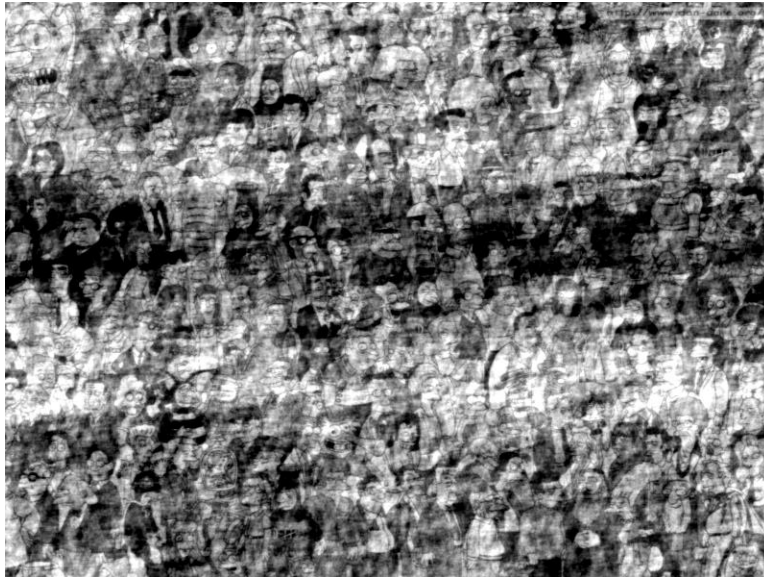


Figure 6: Magnitude of Zebra picture with Phase of Simpsons picture

Problem 7

Pictures for the Zebra image



Figure 7: Magnitude of the Gradient of the zebra picture where $\sigma = 3$

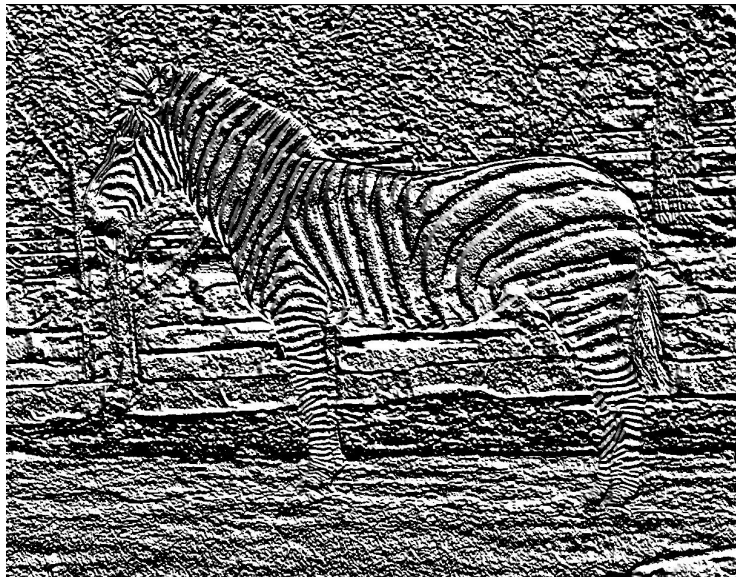


Figure 8: Orientation of the Gradient of the zebra picture where $\sigma = 3$

With new sigma



Figure 9: Magnitude of the Gradient of the zebra picture where $\sigma = 2$

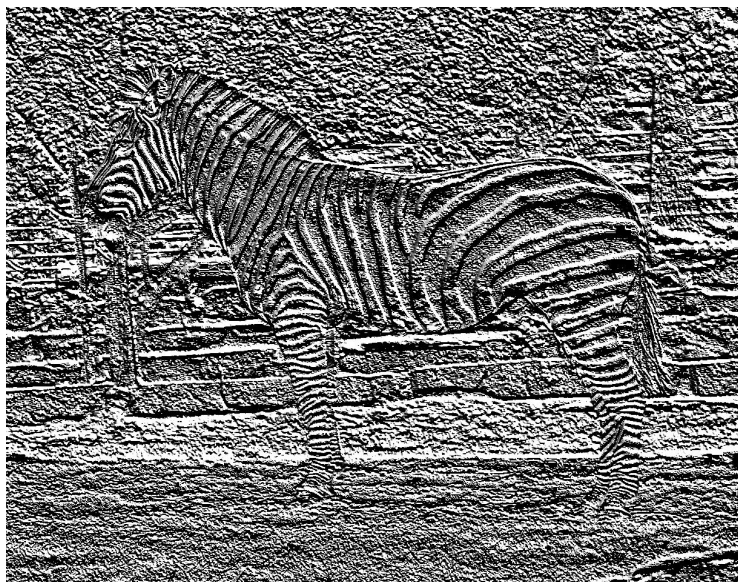


Figure 10: Orientation of the Gradient of the zebra picture where $\sigma = 2$