HW2

1) i)(f[n]*g[n])*h[n] =
$$\sum_{l=-\infty} t_0 \infty (f^*g)[l] h[n-l]$$

= $\sum_{l=-\infty} t_0 \infty \sum_{k=-\infty} t_0 \infty f[k] g[l-k] h[n-l]$

ii)
$$f[n] * (g[n]*h[n]) = \sum_{p=-\infty \text{ to } \infty} f[p] (g*h)[n-p]$$

= $\sum_{p=-\infty \text{ to } \infty} f[p] \sum_{q=-\infty \text{ to } \infty} g[q] h[n-p-q]$

$$= \sum_{p=-\infty \text{ to } \infty} \sum_{q=-\infty \text{ to } \infty} f[p] g[q] h[n-p-q]$$

Substitute p = k & q = l - k; The i) and ii) are equal.

2) Use a counter example to show that correlation is not associative.

Correlation: $\sum_{k=-\infty} t_0 \infty f[k]g[n+k]$

Results:

3) Spatial Domain Approach: Calculating a single pixel of output image will take M x N multiplications. The output image contains H x W pixels. Therefore, the runtime of 2D convolution is O(MxNxHxW).

Frequency Domain Approach: Multiplication in frequency domain is O(MxN). FFT transform for the image is O(MxN log(MxN)). FFT transform for the filter is O(HxW log(HxW)).

Total run time of $2xFFT + frequency domain multiplication is: <math>2x[O(MxN) \log(MxN)) + O(HxW \log(HxW))] + O(MxN)$

Example: Given M = N = H = W = 256;

Spatial Domain Approach: 4.29 x 10⁹ operations

Frequency Domain Approach: 1,328,147 operations

4)

$$\textstyle \sum_{j=-\infty} {}_{to} \, {}_{\infty} \, \textstyle \sum_{i=-\infty} {}_{to} \, {}_{\infty} \, r[i,\,j] \, \, f[m-i,\,n-j]$$

=
$$\sum_{j=-\infty \text{ to }\infty} \sum_{i=-\infty \text{ to }\infty} r[i,j] f_1[m-i] f_2[n-j]$$

=
$$\sum_{j=-\infty \text{ to }\infty} f_2[n-j](\sum_{i=-\infty \text{ to }\infty} r[i,j] f_1[m-i])$$

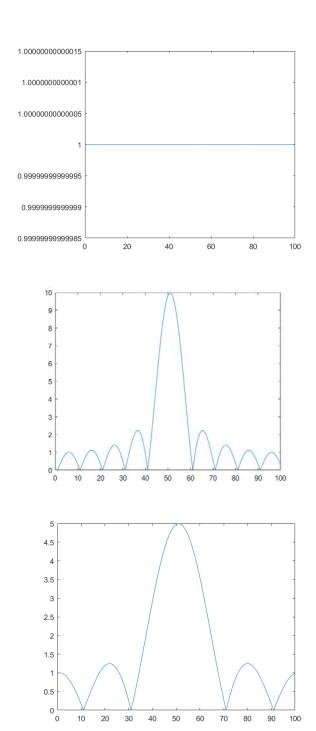
2D Isotropic Gaussian Filter

$$g(x,y) = (1/(2\pi\sigma^2)) \exp ^{(-(x^2+y^2)/(2\sigma^2))}$$

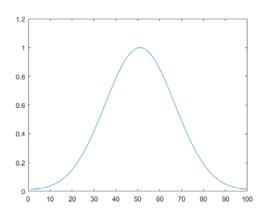
=
$$(1/(2\pi\sigma^2)) \exp^{-(-x^2/(2\sigma^2))} \exp^{-(-y^2/(2\sigma^2))}$$

$$= (1/(2\pi\sigma^2)) g_1(x)g_2(y)$$

5) DTFT of unit box function with 1, 5, and 10 samples.



Gaussian function with sigma = 1 & 2 moved to DFT.



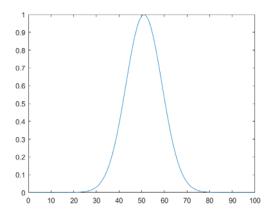


Image 1:



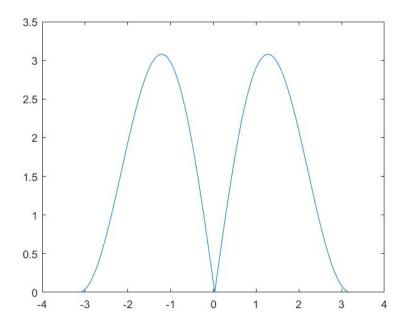
Image 2:



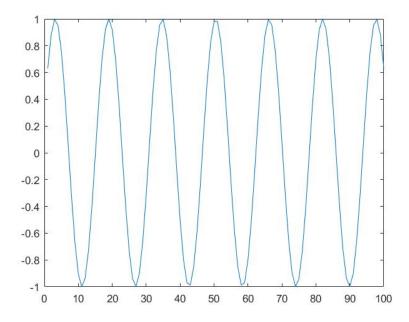
Grayscale Combination (Image 1 magnitude + Image 2 phase):



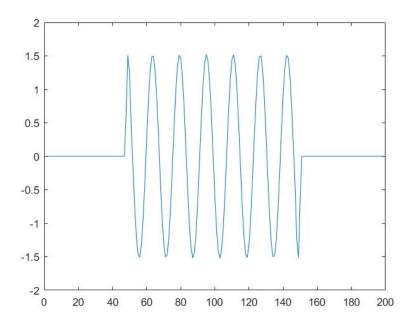
Other (experimented with a simple high pass filter): High Pass Filter [1 1 -1 -1]:



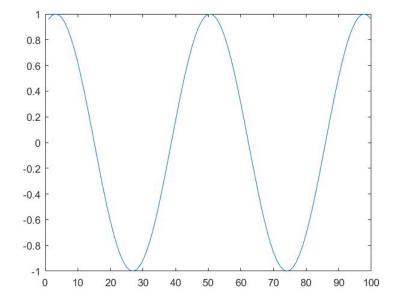
Input (cos(pi/2)*x):



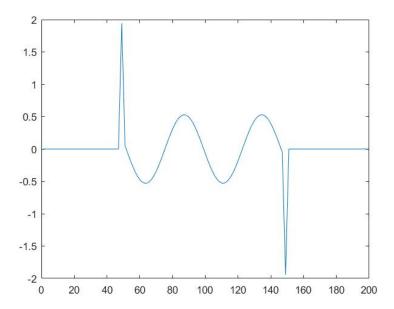
Output:



Input $(\cos(pi/6)*x)$:



Output:



Higher frequencies (from the input) were scaled up while lower frequencies (from the input) were scaled down when input was convolved with the high pass filter.

6) Original Image:



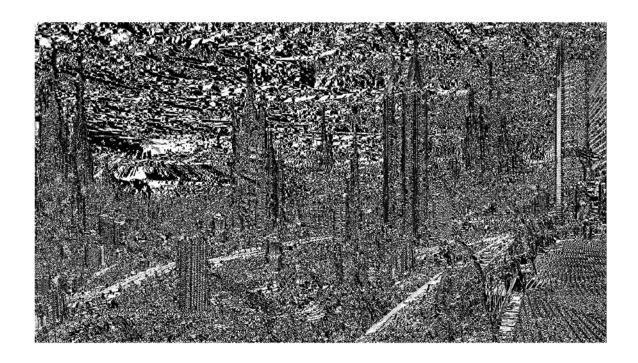
Smooth Image (Sigma 1):



Gradient Magnitude (Sigma 1):



Gradient Orientation (Sigma 1):



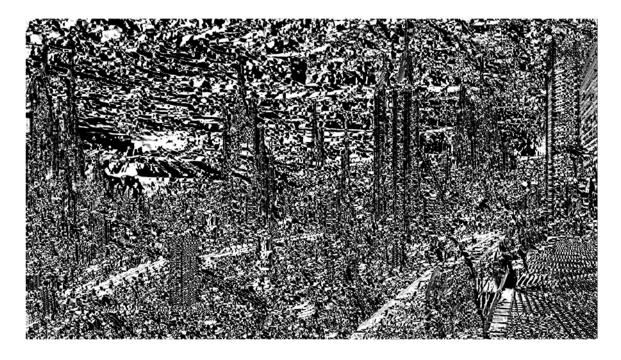
Smooth Image (Sigma 2):



Gradient Magnitude (Sigma 2):



Gradient Orientation (Sigma 2):

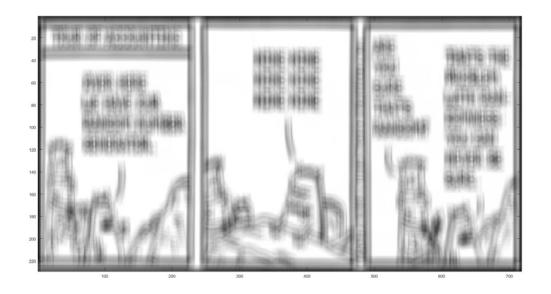


7)

Template (letter 'E' after being flipped left to right & upside down):

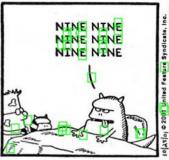
3

Result of convolution between the original Dilbert image & letter E:



Best detections achieved (using convolutional approach):







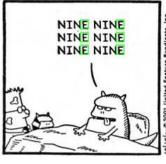
8)

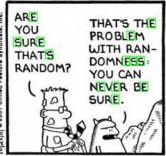
Template (same as in part 7):

3

Best Detections using convolution & SSD:







SSD based object detection method performs significantly better than the correlation via convolution method. One of the reasons that SSD

based object detections performs better is that it avoids the problem of white space matching. This is an issue that I have described briefly in the comments within the detect_template_correlation.m file.

Bonus:

Within detect_template_correlation.m I have written another approach toward object detection using corr2 function. This method has better performance than correlation via convolution or SSD. It is also the slowest of all 3 methods.

Results:



