

**EE640 STOCHASTIC SYSTEMS  
 SPRING 2008  
 COMPUTER PROJECT 1A**

**PART A: SYNTHESIS(4-8-08, 3-24-2010)**

**A.1 GENERATING GAUSSIAN NOISE FROM UNIFORM NOISE**

Let  $N_x = M_y = 128$ :

1. Uniform pseudo-random numbers. Generate 6 random images, each with a different seed. The images are all  $M_y \times N_x$  where each element is uniformly distributed between 0 and 1. Each element is independent from the others. Let  $N = M_y \times N_x$ . Mathematically refer to the images as  $N \times 1$  vectors in lexicographical form as:

$$\underline{u}_1, \underline{u}_2, \underline{u}_3, \underline{u}_4, \underline{u}_5, \underline{u}_6 \quad (\text{A-1})$$

2. Prove the parametric transformation equations for converting from a uniform distribution to a gaussian distribution are correct.

$$\underline{g}_i[2n+1] = \sqrt{-2 \ln \underline{u}_i[2n+1]} \cos 2\pi \underline{u}_i[2n+2] \quad (\text{A-2})$$

$$\underline{g}_i[2n+2] = \sqrt{-2 \ln \underline{u}_i[2n+1]} \sin 2\pi \underline{u}_i[2n+2] \quad (\text{A-3})$$

where  $n=0,1,2, \dots, (N/2 -1)$ .

3. Generate six  $M_y \times N_x$  gaussian random images from the associated images in part A.1.1. Use the transformation developed in A.1.2. Generate them with a 0 mean and unity variance and store as you did in A.1.1. Refer to them in lexicographical form as

$$\underline{g}_1, \underline{g}_2, \underline{g}_3, \underline{g}_4, \underline{g}_5, \underline{g}_6 \quad (\text{A-5})$$

4. Linear combinations of r.v.s. Generate five  $M_y \times N_x$  images such that

$$\begin{aligned} \underline{s}_1 &= \underline{u}_1 + \underline{u}_2 & \underline{s}_4 &= \underline{u}_1 + \underline{u}_2 + \underline{u}_3 + \underline{u}_4 + \underline{u}_5 \\ \underline{s}_2 &= \underline{u}_1 + \underline{u}_2 + \underline{u}_3 & \underline{s}_5 &= \underline{u}_1 + \underline{u}_2 + \dots + \underline{u}_6 \\ \underline{s}_3 &= \underline{u}_1 + \underline{u}_2 + \underline{u}_3 + \underline{u}_4 \end{aligned} \quad (\text{A-6})$$

Display your results in a way that is suitable for visualizing them. In the next project 1B, you will analyze your synthetic data.

## A.2 GENERATING CONTROL NOISE FROM DETERMINISTIC DATA

There are 23 target and clutter images which are saved in target.zip and clutter.zip, respectively. The size of each image is  $128 \times 128$  pixels. Choose one target and one clutter image from the two classes. Fig. 1 shows an example of 5 target training and Fig. 2 shows 5 examples of clutter images.



Figure 1: Five samples of the 23 target images.



Figure 2: Five samples of the 23 clutter images.

1. Find the PSD envelope of your target and clutter images by taking the 2-D Discrete Fourier Transform, then select the magnitude of the resulting spectra and refer to it as  $H_t$  for the target and  $H_c$  for the clutter image. We want to generate noise with an equivalent PSD.
2. Generate two independent  $M_y \times N_x$  uniform noise images,  $A_t$  and  $A_c$ , with element ranges between 0 and  $2\pi$ . Combine these with  $H_t$  and  $H_c$  such that the magnitude of each element is the same as  $H_t$  and  $H_c$  but the phase angle of the complex elements is determined by the two random images  $A_t$  and  $A_c$ , respectively. Inverse the result back to space domain and display the noise images.
3. Generate two independent  $M_y \times N_x$  Gaussian noise images,  $g_t$  and  $g_c$  with element values having zero mean and unit variance. 2-D DFT these images to get  $G_t$  and  $G_c$  spectra. Elementwise multiply these spectra by  $H_t$  and  $H_c$ , respectively. Then inverse DFT the result back to the space domain and display results.
4. Are the noise images pairs, in task 2 and 3, statistically equivalent? Show why or why not, mathematically.

### A.3 DIGITAL STOCHASTIC SIGNAL IMAGES

1. Generate two image vectors, a pseudo-random binary (i.e., bipolar) sequence and pseudo-random intensity sequence such that:

$$\underline{b}_{binary}[n] = \begin{cases} 1 & \text{for } \underline{u}_1[n] \geq 0.5 \\ -1 & \text{for } \underline{u}_1[n] < 0.5 \end{cases} \quad (\text{A-7})$$

and

$$\underline{s}_{intensity}[n] = \left(\underline{g}_1[n]\right)^2 \quad (\text{A-8})$$

where  $n=1,2,\dots,N$ . The size of the images in 2-D is the same as in A.2.

Display these images so it is easy to visualize the difference in the noise types.

#### APPENDIX

If you encode noise into the frequency domain and require that the inverse fft yields all real values in the “space” or “time” domain, then there must be certain symmetry conditions met in the frequency domain. To demonstrate this, create an 8x8 matrix, A, of random noise. Then fft it to the frequency domain as B and evaluate the symmetry within the real and imaginary components.

A =

0.9501	0.8214	0.9355	0.1389	0.4451	0.8381	0.3046	0.3784
0.2311	0.4447	0.9169	0.2028	0.9318	0.0196	0.1897	0.8600
0.6068	0.6154	0.4103	0.1987	0.4660	0.6813	0.1934	0.8537
0.4860	0.7919	0.8936	0.6038	0.4186	0.3795	0.6822	0.5936
0.8913	0.9218	0.0579	0.2722	0.8462	0.8318	0.3028	0.4966
0.7621	0.7382	0.3529	0.1988	0.5252	0.5028	0.5417	0.8998
0.4565	0.1763	0.8132	0.0153	0.2026	0.7095	0.1509	0.8216
0.0185	0.4057	0.0099	0.7468	0.6721	0.4289	0.6979	0.6449

B=fft2(A);

real(B)=

3/24/2010

EE640 PROJECT 1

33.5960	2.5077	1.4570	-2.7182	-0.8693	-2.7182	1.4570	2.5077
-1.1868	-2.5328	-1.0442	-0.3453	0.8548	-0.5695	-0.9498	0.5963
2.0612	-0.2416	1.2408	2.2483	0.8064	-1.4776	1.4948	0.0927
1.5700	0.1783	-1.1027	3.3849	0.9106	-0.3712	-1.7902	3.3390
0.0120	1.3609	1.9355	2.6287	-0.6061	2.6287	1.9355	1.3609
1.5700	3.3390	-1.7902	-0.3712	0.9106	3.3849	-1.1027	0.1783
2.0612	0.0927	1.4948	-1.4776	0.8064	2.2483	1.2408	-0.2416
-1.1868	0.5963	-0.9498	-0.5695	0.8548	-0.3453	-1.0442	-2.5328

Note that the for a column index  $n=1,2,\dots,N$  and a row index  $m=1,2,\dots,M$ , that if  $m=1$  and  $n>N/2$  then  $\text{real}(B(m,n))=\text{real}(B(m,n_1))$  where  $n_1=2+N-n$ . The same is true for the column index such that if  $n=1$  and  $m>M/2$  then  $m_1=2+M-m$ , so that  $\text{real}(B(m,n))=\text{real}(B(m_1,n))$ .

$\text{imag}(B)=$

0	0.5449	-1.3813	3.1988	0	-3.1988	1.3813	-0.5449
-1.0333	-1.0398	0.6684	1.8551	-0.7279	-0.2027	-0.8158	0.4521
0.1559	-2.0416	-2.9714	-0.5650	-1.3007	2.7827	0.6965	-0.6664
0.3264	-0.9061	0.4175	1.0483	-1.8740	-0.7414	2.5313	0.7601
0	0.3909	-3.4593	2.7975	0	-2.7975	3.4593	-0.3909
-0.3264	-0.7601	-2.5313	0.7414	1.8740	-1.0483	-0.4175	0.9061
-0.1559	0.6664	-0.6965	-2.7827	1.3007	0.5650	2.9714	2.0416
1.0333	-0.4521	0.8158	0.2027	0.7279	-1.8551	-0.6684	1.0398

Note that the for a column index  $n=1,2,\dots,N$  and a row index  $m=1,2,\dots,M$ , that if  $m=1$  and  $n>N/2$  then  $\text{imag}(B(m,n)) = -\text{imag}(B(m,n_1))$  where  $n_1=2+N-n$ . The same is true for the column index such that if  $n=1$  and  $m>M/2$  then  $m_1=2+M-m$ , so that  $\text{imag}(B(m,n)) = -\text{imag}(B(m_1,n))$ .