Advanced Digital Signal Processing: Imaging and Image Processing



Exercise 5: Image Modeling and Reconstruction

Due date: 21.07.2015

Problem 1 - Gibbs Sampler for a Gaussian Distribution

In this problem you will investigate the Gibbs sampler by implementing it for a Gaussian bivariate distribution given by

$$p(\mathbf{x}) = \frac{1}{2\pi\sqrt{\det \Sigma}} \exp\left\{-\frac{1}{2} \left(\mathbf{x} - \boldsymbol{\mu}\right)^T \boldsymbol{\Lambda} \left(\mathbf{x} - \boldsymbol{\mu}\right)\right\} \quad \text{with} \quad \mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}.$$

where μ denotes the mean vector and $\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{12} & \lambda_{22} \end{bmatrix} = \Sigma^{-1}$ the precision matrix. The conditional probability $p(x_1|x_2)$ is

$$p(x_1|x_2) \propto \mathcal{N}(x_1|\mu_1 - \frac{\lambda_{12}}{\lambda_{11}}(x_2 - \mu_2), \lambda_{11}^{-1}).$$

a) Use the conditional probabilities $p(x_1|x_2)$ and $p(x_2|x_1)$ to generate samples from $p(\mathbf{x})$ in MATLAB using Gibbs Sampling. Use **randn(1)** to sample from a univariate Gaussian distribution. Remember that x_1 and x_2 are sampled in turns and therefore depend on each other. You can initialize x_1 and x_2 with arbitrary values. Use

$$\mu = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$$
 and $\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

- b) Plot the samples using the command **scatter** and compare them with the shape of $p(\mathbf{x})$. Use **mvnpdf** and **contour** to create a plot of $p(\mathbf{x})$.
- c) Repeat with

$$\Sigma = \begin{bmatrix} 1 & 0.9 \\ 0.9 & 1 \end{bmatrix}$$

and comment on your observation drawing 10 samples. What do you observe regarding the samples? Are the samples drawn by the Gibbs sampler distributed as expected?

- d) Why is Gibbs sampling often easier than sampling from the original distribution?
- e) What is the drawback of Gibbs sampling?

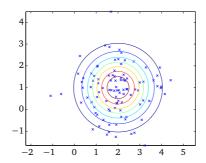


Figure 1: Samples drawn from $p(\mathbf{x})$.

Problem 2 - Gibbs Sampler for the Ising Model

Images are usually modeled as a regular grid of random variables. Here, we consider only a binary image denoted by $\mathbf{X} \in \{-1,1\}^{N_1 \times N_2}$ where N_1 and N_2 denote the image size. In this task, you will draw samples from the Ising Model that describes the relations between the random variables to generate pseudo-images. Considering the Ising model, \mathbf{X} is distributed as follows.

$$p(\mathbf{X}) = \frac{1}{Z} \prod_{i=1}^{N_1} \prod_{j=1}^{N_2} \exp \{ \beta \cdot \sum_{(i',j') \in \mathcal{N}_{(i,j)}} \delta(x_{(i,j)}, x_{(i',j')}) \}$$

where

$$\mathcal{N}_{(i,j)} = \{(i-1,j), (i+1,j), (i,j-1), (i,j+1)\} \quad 1 \le i \le N_1, 1 \le j \le N_2$$

denotes the first order neighborhood of the (i, j)th-pixel. Note that $\delta(x, x')$ counts similar neighbors and is defined as

$$\delta(x, x') = \begin{cases} 1 & \text{for } x = x' \\ 0 & \text{otherwise} \end{cases}$$

a) Calculate the conditional probability

$$p(x_{(i,j)} = +1 | \mathbf{X}_{\setminus (i,j)}) = \frac{p(x_{(i,j)} = +1, \mathbf{X}_{\setminus (i,j)})}{\sum_{x_{(i,j)} \in \{-1,1\}} p(x_{(i,j)}, \mathbf{X}_{\setminus (i,j)})}$$

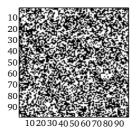
with $1 \le i \le N_1$ and $1 \le j \le N_2$.

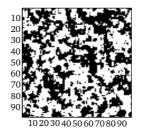
Hint: The conditional is of the form $\frac{1}{1+\exp\{V_{(i,j)}(\beta)\}}$ where $V_{(i,j)}(\beta)$ depends on β and the neighborhood of $X_{(i,j)}$ (*Pen & Paper*).

Given the conditional distribution, we can now implement the sampler in MATLAB.

- b) Generate a matrix **X** of size 100×100 and initialize it by uniformly distributed random values in $\{-1, +1\}$.
- c) For every element $x_{(i,j)}$, compute the conditional probability $p(x_{(i,j)} = +1 | \mathbf{X}_{\setminus (i,j)})$.
- d) Next, assign $x_{(i,j)} = +1$ with probability $p(x_{(i,j)} = +1 | \mathbf{X}_{\setminus (i,j)})$ and $x_{(i,j)} = -1$ otherwise. Use **rand** to generate a random number.

e) Repeat this process with N=1000 iterations and observe how the image is generated. Try different values for β and shortly comment on your results. For testing, set $\beta=1$.





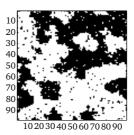


Figure 2: Image after 1, 5 and 50 iterations (from left to right).