# ECE505 Computer Project I

Due Date: Nov. 5, 2024

In this project you will experiment with various algorithms that you have learned in class for unconstrained optimization.

Implement your procedures on a computer. Use any programming language at will. At the end you will submit a project report, in which you should by all means document your implementation clearly and concisely. For example, what is the principle of your algorithm? how would you determine its parameter(s) if necessary? Be sure to discuss and comment on your test results. Your results should be presented using graphs and tables whenever applicable.

You project report will be graded based on the following bases: correct, clear, and concise. **Limit your report to no more than 10 pages**.

## Part 1. Algorithmic Implementation

*1. Steepest Descent Algorithm.* See Problem 10 in the document 'prob10.pdf' for details. For 10.(a) you may use any of the linear search algorithms covered in class.

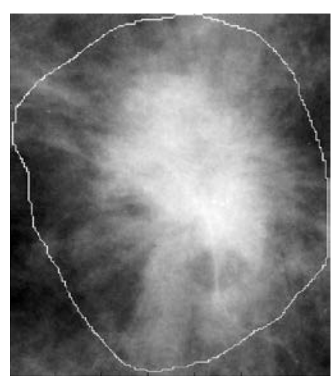
*2. Newton Algorithm.* Test your algorithm using the same problems as in 10.(d).

*3. BFGS Quasi-Newton Algorithm.* See Problem 11 in the document 'prob11.pdf' for details. For 11.(a) you may use any of the linear search algorithms covered in class.

*4. Conjugate Gradient Algorithm*. For line search, you may use any of the linear search algorithms covered in class.

## Part 2. Application (optional)

Assume the intensity value (i.e. brightness) of a pixel in a cancerous region in a mammogram image can be modeled by a Gaussian $N(\mu_1, \sigma_1^2)$, where $\mu_1, \sigma_1^2$ are the mean and variance of the intensity, respectively, while that in a harmless background is modeled by a Gaussian $N(\mu_2, \sigma_2^2)$. A uniform random sampling of a mammogram image (shown below) yields 200 intensity values from the image (listed in a separate spreadsheet). Based on this information, estimate the proportion of cancerous pixels in this image.



*Hint:* Let $P_1$ denote the proportion of cancerous pixels in the image. Then a randomly chosen pixel from the image has the following distribution

$$p(x; \mu_1, \sigma_1^2, \mu_2, \sigma_2^2, P) = P_1 \cdot \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} + (1 - P_1) \cdot \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}}.$$

The problem then is to estimate the unknowns $\Theta = \left(\mu_1, \sigma_1^2, \mu_2, \sigma_2^2, P_1\right)$ from the given image samples. You may consider finding the *maximum-likelihood estimate* (MLE)

$$\left(\mu_1, \sigma_1^2, \mu_2, \sigma_2^2, P_1\right) = \arg\max_{\Theta} \left( \prod_{i=1}^{200} p\left(x_i; \mu_1, \sigma_1^2, \mu_2, \sigma_2^2, P\right) \right),$$

where $x_i, i = 1, 2, \cdots, 200,$ denote the image samples.