Chapter 3

Breast cancer—Segmentation of micro-calcifications

3.1 Introduction

The smallest of these (under 1 mm in diameter) are called micro-calcifications and represent some of the earliest signs of breast cancer. Micro-calcification clusters may be the only indication of in-situ tumors. Approximately 80% of micro-calcifications are benign, their shape and topology differentiating them from the malignant type.

In general, micro-calcification detection algorithms consist of three stages: (i) a preprocessing step based on filtering the image, which consists of subtracting a signal-enhanced image from a signal-suppressed image (ii) a segmentation step, which consists of global thresholding and morphological erosion, or region growing or adaptive thresholding; and (iii) a clustering step, which uses typically a fixed size kernel to eliminate noise points and isolates the calcifications and identify the clusters. A major drawback of these methods is their poor sensitivity to small and faint micro-calcifications. Here, foveal segmentation algorithm is used which gives satisfactory results.

3.2 Segmentation of micro-calcifications

The Foveal segmentation algorithm that is based on a biological model of adaptive contrast-detection, complemented with complex pre-processing steps. The rationale for adopting a model inspired from the human visual system is due to the challenge posed by the highly variable mammogram image background especially when bright micro-calcifications are hidden within bright dense tissue.

3.2.1 Human Visual System (HVS)
The adaptation of the eye to light changes is a continuous process in the HVS. We perceive objects differently if they are against a bright surface or dark area. The adaptation luminance is the response of the eye in adding an average luminance within the central visual field or fovea ($L_{foh}$) and an equivalent veiling luminance caused by surfaces surrounding the peripheral field of view ($L_{seq}$) as given by

$$L_a = L_{foh} + L_{seq}$$

However, foveal adaptation stems mainly from the luminance within the foveal field and relates approximately only ten percent to the luminance of the field of view outside of the fovea [78]. Furthermore, the visual perception of the eye is dependent on the spatial perception of the object we visualize. This effect is called lightness assimilation. The same object may appear lighter on a dark background and darker over a light surface as shown in Fig. 3.1. The eye is still perfectly capable of distinguishing the three central areas, but this is not obvious for a computer program.

![Fig. 3.1: An illustration of the lightness assimilation.](image)

The three synthetic images are shown with dark (left), medium (middle) and bright (right) backgrounds. All have central objects of the same size and intensity, but are perceived differently by our eyes, due to the variance in the background lightness.

### 3.2.2 Visual Perception based Segmentation

#### A. Brightness Stimuli

The simulation of the retina involves showing regions with different brightness stimuli: fovea centralis object background and surround background. The regions are arranged as concentric circles, with the fovea centralis in the middle followed by the object background and the surround background. The fovea centralis is the observation field that is always focused on the
object of interest by the accommodation ability of the eye. In the biological system, the receptors of illumination are directly connected to the next neural layer to achieve an optimal representation of the environment. The brightness stimulus of the fovea centralis can be simplified as

\[
\lambda_0(x,y) = \frac{1}{K \times K} \sum_{m=-K}^{K} \sum_{n=-K}^{K} I(x-m,y-n)
\]  

(3.2)

Where \( I(x,y) \) are the gray intensity of the considered pixel \((x, y)\) \(N_0 \) is the number of pixels in the simulated fovea centralis and a change of \( \lambda_0 \) represents the accommodation ability. It can be adjusted for different object sizes and remains constant during the segmentation process.

The object background is the close neighborhood of the fovea centralis that has a strong influence on the perception of the object. In regions outside of the fovea centralis, the retina consists of receptive fields with a center and neighborhood points with a lower influence. Therefore, the brightness stimulus of the object background can be simplified and expressed as the weighted intensity of the region in (3.2) its size is biologically motivated [75] as in the following:

\[
\lambda_s(x,y) = \frac{1}{\sum_{m=-n}^{n} \sum_{n=-n}^{n} \frac{\sqrt{(x-m)^2 + (y-n)^2}}{i(x-m,y-n)}}
\]

(3.3)

The surround background consists of the area of the complete retina. The weak influence of the retina’s parts far away from the fovea centralis makes it reasonable to consider the average gray level of the whole image as the stimulus of the surround background (3.45) [76]:

\[
\lambda_b = \frac{1}{M \times N} \sum_x \sum_y I(x,y)
\]

(3.4)

B. Contrast Perception

Contrast is the perceived difference in luminance between objects and background. According to Weber’s Law [76], the contrast (3.5) refers to the normalized difference between the brightness stimuli of the fovea centralis and the object background.
\[ C = \begin{cases} \frac{\lambda_N - \lambda_D}{\lambda_N}, & \text{if } \lambda_D > \lambda_N; \\ 0, & \text{otherwise} \end{cases} \quad (3.5) \]

C. Adaptation

The human eye has the ability to adapt to different illuminances in a wide range. According to Moon and Spencer [78], the adaptation illuminance for any light distribution in the field of view can be calculated from

\[ \lambda_0 = \frac{K}{\pi} \int_0^\pi \int_0^\pi \frac{H(\theta, \phi)}{\theta^2} \sin \theta \cos \theta \, d\theta d\phi \quad (3.6) \]

Holladay's principle [77] allows for a considerable simplification, since a non-uniform illumination distribution can be replaced by a uniform distribution that gives the same adaptation illuminance. Given this simplification and the results of psychovisual experiments with geometrical arrangements as in [77-78], Eqn. (3.6) can be transformed into

\[ \lambda_A = 0.923 \lambda_N + 0.77 \lambda_B \quad (3.7) \]

D. Minimal Perceptible Contrast

The minimal perceptible contrast is defined as the normalized amount of light that must be added to a brightness stimulus of the fovea centralis so that it can just be discriminated from a reference field of the same brightness stimulus:

\[ C_{\min} = \frac{\Delta \lambda_{\min}}{\lambda_B} \quad (3.8) \]

The minimal perceptible contrast is a function of the adaptation illuminance. Moon and Spencer [78] have proposed the first reliable expression for the minimal perceptible contrast by maximum illuminance.

\[ C_{\min}(x, y) = \begin{cases} C \left( \frac{1}{\lambda_D(x, y)} \right)^{0.808} \sqrt{\lambda_D(x, y)}, & \text{when } \lambda_D(x, y) > \lambda_D(x, y) \\ C \left( \frac{1}{\lambda_D(x, y)} \right)^{0.808} \sqrt{\lambda_D(x, y)}, & \text{when } \lambda_D(x, y) \leq \lambda_D(x, y) \end{cases} \quad (3.9) \]

The above model is used for segmentation. To simulate the biological accommodation, the artificial fovea centralis will be moved through the image in order to calculate once for every pixel. A part of the scene is considered as an object if the fovea centralis can perceive it. That means if the pixel value is greater than the minimal perceptible contrast, the pixel belongs to the
object. An optimal segmentation is set manually for a group of images. To detect objects of different sizes, the area of the fovea centralis and the object background can be adjusted.

### 3.2.3 Local Background Subtraction Technique

At first, the mammogram is considered as a three-dimensional plot with the third axis (z) corresponding to the intensity of each pixel. The whole image is split up into 30 x 30 sub-regions. Histogram is formed for each of the sub-regions. From the histogram we find the threshold which maximizes the Shannon’s entropy. We used bi-cubic interpolation to obtain the second plot representing the intensity level of the local background. The interpolated image is subtracted from the original mammogram producing a third image with each pixel value providing the difference between the original and local background pixel values. The image is normalized to range 0-255 and subjected to filtering.

#### A. Filtering using Laplacian of Gaussian Filter

The Laplacian is a 2-D isotropic measure of the second spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. The Laplacian is often applied to an image that has first been smoothed with an approximate Gaussian smoothing filter in order to reduce its sensitivity to noise. The Laplacian operator normally takes a single gray level image as the input and produces another gray level image as the output.

The Laplacian $L(x, y)$ of an image with pixel intensity values $I(x, y)$ is given by:

$$L(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

(3.10)

Using an appropriate convolution kernel, the Laplacian can be evaluated using the standard convolution methods.

The kernel approximates a second derivative measurement on the image, which is very sensitive to noise. To counter this, the image is often Gaussian smoothed before applying the Laplacian filter. This pre-processing step reduces the high frequency noise components prior to the differentiation step [79]. Since the convolution operation is associative, we convolve the
Gaussian smoothing filter with the Laplacian filter first, and then convolve this hybrid filter with the image to achieve the required result.

The 2-D LoG function centered on zero with the Gaussian standard deviation $\sigma$ has the form:

$$LoG_{\sigma}(x, y) = \frac{1}{\pi\sigma^4} \left( 1 - \frac{(x^2 + y^2)}{2\sigma^2} \right) e^{-\frac{(x^2 + y^2)}{2\sigma^2}}$$

(3.11)

The discrete version of the filter suitable to be applied on digital images is of the form:

$$LoG_{\sigma}(i, j) = \frac{(i^2 + j^2 - 2\sigma^2)h_g(i, j)}{2\Pi\sigma^6\sum_i\sum_j h_g}$$

(3.12)

A discrete kernel that approximates the Gaussian function with $\sigma = 1.7$ having a size of 51 x 51 pixels is chosen in our case. In our approach the input signal is fed to LoG filter set to the standard deviation of 1.7

$$G = LoG_{\sigma=1.7} * I$$

(3.13)

Where $G$ is the response of the filtering. The effect of this operation is the increase in the contrast of the micro-calcifications.

The local contrast measure $C$ of each pixel is estimated and compared with a threshold value $C_T$ and if $C$ of the pixel is found to be greater than $C_T$ then the pixel of interest is labeled as micro-calcification pixel. The local contrast is defined as the difference between the maximum value of the window surrounding the pixel and the pixel of interest. The value of $C_T$ used is 55. The resulting image is a binary image showing the white regions as the micro-calcifications.

The segmentation algorithm is applied to the regions of interest containing micro-calcifications. Fig. 3.2(a) shows the mass ROI and Fig. 3.2(b) show the segmented image by foveal algorithm. Figure 3.2(c) shows the images segmented by LoG filter with background subtraction.
3.3 Conclusions

Micro-calcifications exist in different portions of mammogram. Some part of the mammogram is dense and some portion is normal. It is very difficult to detect the micro-calcifications from the region of interest using a fixed threshold. Foveal adaptation technique which is based on human visual system is an adaptive thresholding technique which is found to be more effective in segmenting the micro-calcifications. This method is compared with the LoG filtering technique with background subtraction. There is a substantial reduction of false positives and true negatives.