FUZZY TECHNIQUES FOR CONTRAST ENHANCEMENT OF MAMMOGRAMS

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FUZZY TECHNIQUES FOR CONTRAST ENHANCEMENT OF MAMMOGRAMS

by

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LIST OF ABBREVIATIONS

CAD	Computer-aided Diagnosis
DSM	Distribution Separation Measure
FHH	Contrast Improvement with Fuzzy Histogram Hyperbolization
FIT	Contrast Improvement based on Fuzzy if-then Rules
IEEE	Institute of Electrical and Electronic Engineers
INT	Contrast Improvement with Intensification Operator
MCs	Microcalcifications
MRI	Magnetic Resonance Imaging
PD	Contrast Improvement with Possibility Distribution
ROI	Region of Interest
SD	Standard Deviation
TBC_S	Target-to-Background Contrast Enhancement Measurement Based on Standard Deviation
TBC_ε	Target-to-Background Contrast Enhancement Measurement Based on Entropy

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TEKNIK KABUR UNTUK PENINGKATAN KONTRAS MAMMOGRAM

ABSTRAK

Kanser payudara adalah penyakit utama yang berlaku di kalangan wanita di dunia ini. Pencegahan awal adalah amat sukar kerana faktor yang menyebabkan kanser payudara masih belum dikesan. Jadi, pengesanan awal adalah cara terbaik untuk merawati kanser payudara dan dapat menurunkan angka kematian kanser payudara. Sinar X mamografi adalah kaedah yang diterima pakai bagi mengesan kanser payudara. Namun, tugas mentafsirkan mammogram masih sulit kerana kontras antara kanser payudara dan sekitarnya adalah rendah. Sebab itu, peningkatan kontras bagi mammogram adalah amat perlu. Dalam kajian ini, pendekatan bagi peningkatan kontras bagi mammogram berdasarkan teknik kabur telah dibina dengan menggunakan C++ Builder. Aplikasi ini adalah integrasi daripada teknik peningkatan konvensional dan juga kabur. Implementasi projek terdiri daripada tiga langkah utama, antaranya adalah proses pra-pemprosesan dengan menggunakan teknik peningkatan konvensional, peningkatan mammogram dengan menggunakan teknik peningkatan kabur dan yang terakhir analisis prestasi menggunakan analisis kualitatif dan kuantitatif bagi menilai mammogram yang telah dipertingkatkan. Secara keseluruhan, semua teknik peningkatan kabur mampu meningkatkan kontras mammogram. Namun, prestasi yang ditunjukkan oleh FHH dan INT adalah jauh lebih baik daripada FIT dan PD kerana FHH dan INT dapat mengekalkan maklumat yang terkandung dalam mammogram dengan baik berbanding dengan FIT dan PD.

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ABSTRACT

Breast cancer is the number one disease among women in the world. Primary prevention seems impossible since the causes of breast cancer still remains unknown. However, early detection is the best defensive against breast cancer and it becomes the key to reduce the mortality rate of breast cancer. Today, X-ray mammography becomes the most common method of detecting breast cancer. However, mammography images are still notoriously difficult to interpret due to the fuzzy nature of the mammograms and the low contrast between the breast cancer and its surroundings. Hence, mammogram contrast enhancement is critical and essential in the tasks of mammography images interpretation. In this study, an approach to mammogram contrast enhancement based on fuzzy techniques is build by using C++ Builder. The application is an integration of conventional and fuzzy enhancement techniques. The conventional techniques that are used are linear contrast, power-law transformation, contrast stretching and unsharp mask while the fuzzy enhancement techniques used are FHH, INT FIT and PD. The project implementation consists of three steps; there are image pre-processing by using conventional enhancement techniques, fuzzy enhancement and the last is performance analysis that uses qualitative and quantitative analysis to evaluate the enhanced mammograms. Overall, all fuzzy enhancement techniques are able to enhance the contrast of the mammograms. However, both FHH and INT techniques are better than FIT and PD since FHH and INT can preserve the information contained in mammograms well compared to FIT and PD.

CHAPTER 1
INTRODUCTION

1.1 Overview of Study

Breast cancer is the number one disease among women in the world. In Malaysia, the incidence of breast cancer is on the rising edge and it can strike anyone regardless of color, creed or status. Since the causes cannot been identified, hence breast cancer cannot be prevented. Hence, early finding and treatment must be implemented in order to reduce the mortality rate of breast cancer. Today, several common examinations of breast cancer are available, these include ultrasound, X-ray mammography screening, MRI, etc. However, the most common method of detecting breast cancer is X-ray mammography and this is a screening method that is recommended by experts for use on patients of any age (Kuske, 2010). The screening programs based on mammography have been instituted in most countries around the world due to its effectiveness at detecting cancerous lesions before clinical symptoms appear and cheaper than other modalities like MRI. Such programs aim to increase the effectiveness of treatment by detecting primary tumors while they are still clinically localized. When a tumor becomes palpable, it would very likely have metastasized (Shen, 1998).

Although mammography is one of the most effective methods for early detection of breast cancers, mammography images are still notoriously difficult to interpret (Berman, 2007). First, the imaging system may have serious imperfections. Secondly, screening programs generate large numbers of highly variable, complex images, most of which are unequivocally normal. Significant abnormalities, when present, may be small or subtle. Finally, abnormal regions are often hidden in dense breast tissue. Besides that, visually analyzing these images is an arduous, time consuming, and expensive task. Furthermore, each individual scan is prone to interpretation errors (error rates of radiologists are reported to be as high as around 30%) (Lee, 2007). Consequently, some lesions are missed or misinterpreted (Morton *et al.*, 2006). Therefore, numerous researchers have developed automated breast cancer detection system for radiologists to diagnose breast cancer in its early stages.

Fuzzy set theory has been successfully applied to many fields, such as pattern recognition, control systems, and medical applications. Fuzzy set theory has also been effectively used to develop various techniques in image processing tasks including mammography images (Kerre & Nachtegael, 2000). The existence of inherent “fuzziness” in the nature of these images in terms of uncertainties associated with definition of edges, boundaries, and contrast makes fuzzy set theory an interesting tool for handling these applications (Khademi *et al.*, 2009).

In this study, an approach to mammogram enhancement based on fuzzy techniques is build by using C++ Builder for the analysis of mammography images. The application is consisted of a few conventional image enhancement techniques like linear contrast, contrast stretching, unsharp mask and also some fuzzy image enhancement techniques like FHH and FIT to aid in enhancement of mammograms especially in efforts to improve the contrast of mammograms.

1.2 Problem Statement

Due to its effectiveness, widespread availability and low cost, mammography is still the most commonly used screening tool for breast cancer detection (Mello-Thoms, 2006). According to Chee (2007), there is rising adoption of digital mammography in Asia Pacific. He believes that a large part of this growth has come from the rising level of awareness and education on the importance of breast screening by various government agencies and NGOs. The continuous efforts in organizing breast cancer awareness programmes as well as promoting breast health screening, where patients enjoy subsidies in mammogram screening, has created a demand for better and faster mammogram services. Moreover, the increasing rate of the breast cancer undoubtedly rises up the demand of breast cancer screening services. Due to the demands, there will be a need of greater number of radiologist involve in mammogram interpretation.

However, mammograms interpretation is one of the most difficult tasks in radiology. As mentioned before, serious imperfections of imaging system, variation in breast cancer abnormalities and low contrast of mammogram can cause the problems in mammogram interpretation. Besides that, the tasks in mammogram interpretation are laborious, time consuming as well. Moreover, task repetition and fatigue combine to make missing the subtle signs of breast cancer and thus increase the rate of false positive and false negative. Given these difficulties, a good tool that can help the radiologist in mammography interpretation would be an advantage. Therefore, this work will be relevant for now and for future use.

1.3 Objectives

The main target for this project is to build an application that named Fuzzy Rule Based Image Processor that consists of some conventional and fuzzy image enhancement techniques that can be applied to enhance mammograms. Through the enhancement but without lost of information contained in mammogram, abnormalities like microcalcifications (MCs) can be seen more easier. Hence, the application has potential to be used by radiologists to help them in mammographic interpretation.

The following are the objectives envisioned for this work:

- To build image processing modules and algorithms that would be able to aid in contrast enhancement of mammograms with the consideration of their fuzzy nature.

- To compare the performance of adopted fuzzy image enhancement techniques in this project.

1.4 The Scope of Study

This study mainly focuses on the development of fuzzy rule based image processing algorithm that can aid in the contrast enhancement of mammograms since many mammograms do not have sufficient contrast to allow easy detection of MCs. In this study, conventional image enhancement techniques and fuzzy image enhancement techniques are employed. The fuzzy logic is integrated in fuzzy image enhancement techniques to increase the contrast of MCs. Due to the nature of mammography and breast structure, fuzzy logic would be a better choice to handle the fuzziness of mammograms than traditional methods.

1.5 Report Outline

Overall, this thesis contains a total of five chapters. In the first chapter, a brief explanation regarding the research in this project will be given. This chapter will start with the brief explanation of the background of project, followed by the problem statements, objectives and finally the scope of study.

In Chapter 2, the literature review on conventional and fuzzy image enhancement techniques will be presented. Besides that, two types of performance analysis called qualitative analysis and quantitative analysis that employed in this study will be discussed. For qualitative analysis, the mammogram produced by the fuzzy image enhancement techniques will be observed based on the perception of observer while quantitative analysis uses statistical methods to examine the capability of adopted techniques. A total of four analyses are suggested, namely Distribution Separation Measure (DSM), Target-to-Background Contrast Enhancement Measurement Based on Standard Deviation (TBCs) and Target-to-Background Contrast Enhancement Measurement Based on Entropy (TBCε) will be discussed in the last part of Chapter 2 also.

Chapter 3 will focus on the methodologies of the project. Basically, the project implementation consists of three phases, they are: image pre-processing, implementation of fuzzy image enhancement techniques and the last is performance analysis on the output image. At first, the image pre-processing that used to enhance the contrast of the mammogram, increase the intensity and also sharpen the input mammogram will be discussed. Next, the total of four fuzzy image enhancement techniques that applies different fuzzy approach to enhance the contrast of the mammogram will be dwelled upon. The fuzzy image enhancement techniques that mentioned are Contrast Improvement with Fuzzy Histogram Hyperbolization (FHH), Contrast Improvement with Intensification Operator (INT), Contrast Improvement based on Fuzzy if-then Rules (FIT) and Contrast Improvement with Possibility Distribution (PD). At the end of this chapter, the performance analysis to be used to evaluate the capability of the fuzzy image enhancement techniques will be explained.

Chapter 4 begins with the investigation of best fuzzy image enhancement techniques. First, qualitative analysis is performs on the mammograms after enhanced by enhancement techniques that mentioned. It is done by evaluating the resultant mammogram visually in term of the capability of contrast enhancement, brightness enhancement, and details preserving. Next, the visual inspection is further supported by the quantitative analysis. The results of qualitative and quantitative analysis will be presented and be evaluated as well as the comparison on the enhancement techniques will also be discussed in details.

Finally, in Chapter 5, the conclusion for this project will be discussed. Besides that, the suggestion for future works will also be discussed in this chapter.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Breast cancer is the most common type of cancer in women with the exception of nonmelanoma skin cancers. It is the second leading cause of death by cancer in women, following only lung cancer (American Cancer Society, 2011). As the rate of incidence of breast cancer is increasing all over the world, it is important to use mammography to detect breast cancer earlier, which is associated with higher long term survival rate and now, mammography has become one of the most reliable methods for early detection of breast cancer (Berman, 2007). However, it is difficult for radiologists to do mammogram interpretation due to the fuzzy nature of the mammogram and the low contrast between the breast cancer and its surroundings. Therefore, this work will focus on the enhancement technique for mammogram images.

In this chapter, more details on mammogram image enhancement will be dwelled upon. First, previous enhancement techniques that have been applied on mammogram will be reviewed. Next, conventional image enhancement techniques and the fuzzy image enhancement techniques will be introduced in this chapter also. Last but not least, methods of performance analysis that employed in this study will be discussed in details in the last part of this chapter.

2.2 Image Enhancement of Mammogram

The tasks of image enhancement includes intensity and contrast manipulation, noise reduction, background removal, edges sharpening, filtering, and etc. However, the task of mammogram enhancement is to sharpen the edges or boundaries of ROIs, or to increase the contrast between ROIs and background (Beghdadi & Negrate, 1989). As mentioned, contrast for mammogram is critical and essential for breast cancer diagnosis. It is well-known that if a region differs in luminance from its surroundings by less than 2%, it is indistinguishable to human eye (Dengler *et al.*, 1993). Although MCs usually are brighter than their surroundings, the contrast for some MCs in a dense breast is quite low that human eyes can hardly distinguish them. This is why contrast enhancement techniques take place to increase the contrast of abnormalities like MCs over the threshold. But somehow the contrast enhancement algorithms applied can cause some regions may be under-enhanced while some regions may be over-enhanced and these can lead to serious interpretation error like under-enhancement can cause false negatives and over-enhancement can cause false positive. In this section, work done for mammogram contrast enhancement will be reviewed.

2.2.1 Work Done for Mammogram Contrast Enhancement

Since 1980, works on mammogram enhancement techniques have been started, and it aims to improve the quality and readability of mammograms or to detect abnormalities due to poor contrast of mammograms and visibility of details. Next, the brief for most recent works will be made.

In the year of 2003, Sakellaropoulos *et al.* have proposed a method that based on a spatially adaptive transform of the wavelet coefficients, aimed at overcoming the drawbacks of the method of Laine *et al.* (1994), enhance the contrast of the mammograms and depress the image noise. Furthermore, Heinlein *et al.* (2003) proposed an algorithm for feature enhancement in mammograms using discrete wavelet decompositions called integrated wavelets and the disadvantages of proposed method has been discovered by Scharcanski and Jung (2006) and they improve the early method by developing a wavelet transform based adaptive method for contrast enhancement and noise reduction in mammographic images. In the year 2004, Wirth *et al.* had proposed an approach to enhance the contrast of MCs in mammograms using a contrast enhancement algorithm based on a combination of morphological enhancement and non-flat structuring elements. As well, Stojic *et al.* (2005) proposed a local contrast enhancement technique in digital mammography by using mathematical morphology. Moreover, Salvado and Roque (2005) proposed a method that use wavelet analysis and contrast enhancement by local adaptive operators integrated in the wavelet domain in MCs detection. Besides that, a method that use of moving contrast sweep to enhance the contrast of mammographic image has been proposed by Ngah *et al.* (2008). In the approach of Gorgel *et al.* (2010), the enhancement of mammographic images are based on wavelet denoise and enhancement with homomorphic filtering.

In addition to the methods mentioned earlier, several fuzzy image enhancement techniques have been developed due to the fuzzy nature of the mammography images. In the year 1998 and 2002 respectively, Cheng and Xu had introduced an adaptive fuzzy logic approach to mammogram contrast enhancement. Besides that, Jiang *et al.* (2005) developed a combined approach of fuzzy logic with structure tensors to improve enhancement of presented MCs. Furthermore, a method based on adaptive fuzzy λ enhancement and maximum fuzzy entropy is introduced by Sahba and Venetsanopoulos (2008).

Fuzzy logic is a useful tool for handling the uncertainty associated with vagueness and/or imprecision. Due to imprecise borders, ill-defined shapes and different densities and texture, mammography images are inherently “fuzzy”. Therefore, image processing techniques which incorporate fuzziness in terms of the uncertainty associated with the definition of edges, boundaries and contrast have been evaluated as perfect tools for the analysis of these images.

2.3 Conventional Image Enhancement Techniques

Conventional image enhancement techniques mainly are the global and fix neighbourhood techniques that may adapt to the global features or local features within a fix- neighbourhood and they modify the images based only on global properties (Cheng *et al.*, 2003). The contract stretching techniques, histogram equalization, unsharp masking, and spatial filtering are the major techniques. Conventional image processing techniques do not perform well on mammogram because the enhancement techniques enhanced not only the MCs but also the background and noise. Therefore, only the effective conventional image processing methods that are used in this work will be mentioned in the next section.

2.3.1 Power-Law Transformation

Power-law transformations are useful for general-purpose contrast manipulation and useful to do contrast enhancement on medical images like MRI, mammogram and etc. Power-law transformations have the basic form that shown in Eq. (2.1).

$$s(x, y) = c[r(x, y)]^{\gamma} \tag{2.1}$$

Where c and γ are positive constants and the values of pixels, before and after processing are denoted by r and s, respectively. Plots of s versus r for various values of γ are shown in Figure 2.1.

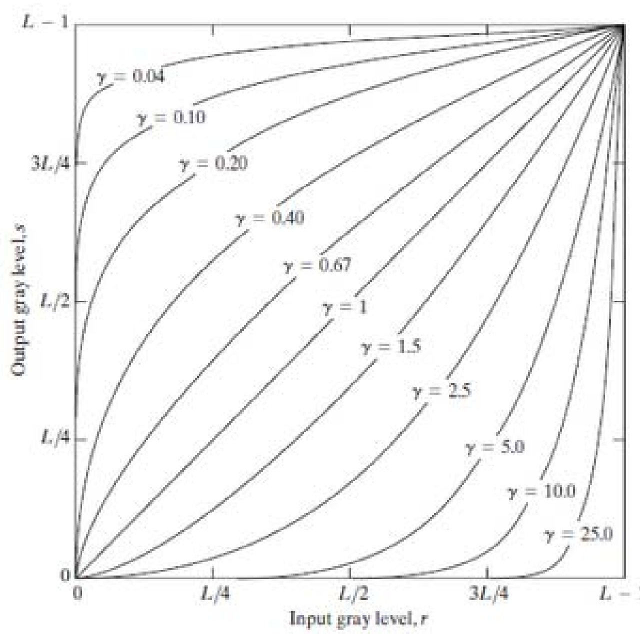

Figure 2.1: Plots of the equation $s(x, y) = c[r(x, y)]^{\gamma}$ for various values of γ (c=1 in all cases). Adopted from Gonzalez & Woods (2002).

With the use of power-law transformation, power-law curves with fractional values of γ map a narrow range of dark input values into a wider range of output values and vice-versa. A special to power-law transformation is family of possible transformation curves can be obtained simply by varying γ and this can be illustrated in Figure 2.1. Two information can be gained from Figure 2.1. One is the curves generated with values of γ >1 have exactly the opposite effect as those generated with values of γ < 1 and another information is the Eq. (2.1) reduces to the identity transformation when $c=\gamma=1$.

2.3.2 Min-Max Linear Contrast Stretch

Follows the Eq. (2.2) that shown as below, when using the min-max linear contrast stretch, the original minimum and maximum values of the data are assigned to a newly specified set of values that utilize the full range of available brightness values. Consider an image with a minimum brightness value of 45 and a maximum value of 205. When such an image is viewed without enhancements, the values of 0 to 44 and 206 to 255 are not displayed. Important spectral differences can be deselected by stretching the minimum value of 45 to 0 and the maximum value of 120. This method is applying with respect to image application type and this method may provide some improvements on the appearance of the image especially dark mammogram images.

$$g(x,y) = \frac{f(x,y) - \min}{\max - \min} \times 255 \qquad (2.2)$$

Where *g(x, y)* represents gray level of output image; *f(x, y)* represents gray level of input image. In this equation the "min" and "max" are the minimum intensity value and the maximum intensity value in the current image.

2.3.3 Contrast Stretching

Sometimes, the impulse noise on the image will affect the performance of min-max linear contrast stretch technique since the technique relies on the minimum and maximum gray level of the image. This type of noise will affect the extreme values used in the scaling of the output image. Besides that, min-max linear contrast stretch technique has its limitation in the sense that user cannot determine the minimum and maximum gray level of the image as threshold in the computation.

To overcome the shortcomings of the min-max linear contrast stretch, contrast stretching is introduced. This technique is more flexible because user can control the minimum and maximum gray levels that act as threshold later. In this technique, pixels with gray level higher than the maximum will set to 255 while pixel with gray level lower than minimum will set to 0 respectively. Then the scaling as in min-max linear contrast stretch will be carried out. The flow chart of the contrast stretching algorithm is shown in Figure 2.2.

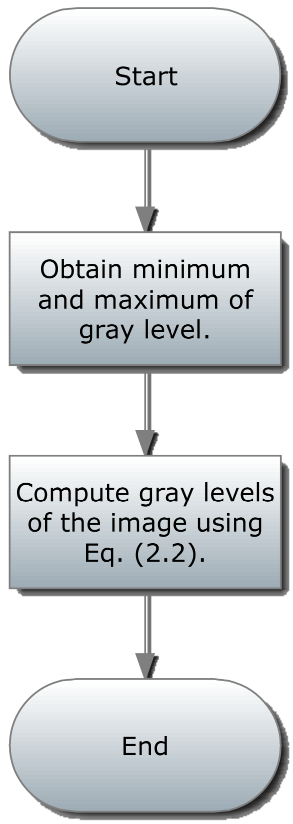

Figure 2.2: Flow chart of the contrast stretch algorithm

Contrast may be improved by gray level scaling where a multiplication operation is used to stretch the histogram to cover the complete range of gray-level values. Such scaling factors are generally constructed in a piecewise-linear fashion. This allows a compressed portion of the histogram to be spread out more than sparsely populated portion of the same histogram. This technique may be used for image restoration to make up for inappropriate image capture and used to achieve optimal usage of the available gray levels.

A histogram of the original image is needed before this technique can be used. To stretch the contrast, the histogram is scanned from the lowest pixel value upward and from the highest pixel value downward to find the first pixel that exceeds a certain threshold.

2.3.4 Median Filter

Median filters are quite popular because, for certain types of random noise, they provide excellent noise-reduction capabilities, with considerably less blurring than linear smoothing filters like mean filter of similar size. Median filters are particularly effective in the presence of impulse noise, also called salt-and-pepper noise because of its appearance as white and black dots superimposed on an image. The calculation of median, ξ is very important in this technique and the median is defined as the value that divides an ordered series of numbers so that there is an equal number of values on either side of the center.

In order to perform median filtering at a point in an image, the following steps need to be taken. First, an ordered series of data (values of the pixel in question and its neighbours) is arranged according to their magnitude. Next, their median is determined follow the definition of median. For example, in a 3*3 neighbourhood the median is the 5^{th} largest value, in a 5*5 neighbourhood the 13th largest value, and so on. When several values in a neighbourhood are the same, all equal values are grouped. Third, the median value is assigned to that pixel. Finally, repeat the steps above to each pixel on the image.

2.3.5 Unsharp Masking

The unsharp filter is a simple sharpening operator which derives its name from the fact that it enhances edges (and other high frequency components in an image) via a procedure which subtracts an unsharp, or smoothed, version of an image from the original image. The unsharp masking is commonly used in the photographic and printing industries for crispening edges and it consists of the following steps:

1. Blur the original image by using median filter that mentioned in previous section.
2. Subtract the blurred image from the original (the resulting difference is called the mask.)
3. Add the mask to the original.

2.4 Fuzzy Image Enhancement Techniques

Fuzzy logic is determined as a set of mathematical principles for knowledge representation based on degree of membership rather than crisp membership of classical binary logic (Zadeh as cited in Negnevitsky, 2005). An image I of size $M \times N$ and L gray levels can be considered as an array of fuzzy singletons, each having a value of membership denoting its degree of brightness relative to some brightness levels l with $l = 0, 1, .., L-1$ (PAL, 1996). A fuzzy singleton is a fuzzy set with only one supporting point. For an image I, we can write in the notation of fuzzy sets as in Eq. (2.3):

$$I = \bigcup_m \bigcup_n \frac{\mu(g_{mn})}{g_{mn}}. \qquad (2.3)$$

Where g_{mn}, is the intensity of (m, n)th pixel and $\mu(g_{mn})$ its membership value. The membership function characterizes a suitable property of image (e.g. edginess, darkness, textural property) and can be defined globally for the whole image or locally for its segments. As we discussed in the previous section, many researchers have applied the concept of fuzziness to develop fuzzy image enhancement techniques that can aid in the process of interpretation of mammogram. Basically, the main principles of fuzzy image enhancement are illustrated in Figure 2.3.

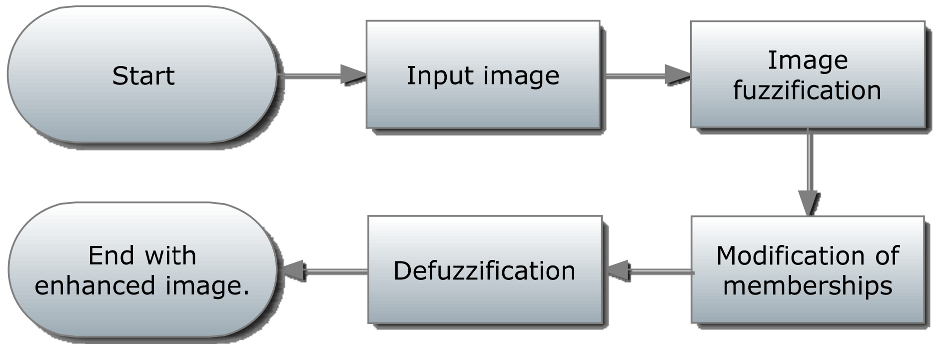

Figure 2.3: The main principles of fuzzy image enhancement

Due to the fact that image is not processed by fuzzy hardware, the coding of image data (fuzzification) and decoding of the results (defuzzification), make possible to process images with fuzzy techniques. For fuzzy image enhancement system as shown in Figure 2.3, the modification of memberships is the most important step compare to others since this step involve of expert knowledge or fuzzy logic which acts as main brain in the system. So, appropriate fuzzy techniques will modify the membership values after all the image data are transformed from gray level plane to membership plane (fuzzification). This can be a fuzzy clustering, a fuzzy rule-based approach, a fuzzy integration approach, and so on.

In this study, total of four fuzzy image enhancement techniques are used and being investigated, they are:

1. Contrast Improvement with Fuzzy Histogram Hyperbolization (FHH)
2. Contrast Improvement with Intensification Operator (INT)
3. Contrast Improvement based on Fuzzy if-then Rules (FIT)
4. Contrast Improvement with Possibility Distribution (PD)

For each fuzzy image enhancement technique, the theoretical knowledge and its implementation will be described in Chapter 3.

2.5 Performance Analysis

To evaluate the performance and the capability of the adopted techniques, performance analyses are performed and compared with the other fuzzy image enhancement techniques. The performance analyses are useful in determining the best technique under certain circumstances, as the adopted techniques are developed using different approaches, which are expected to perform differently for different mammograms.

In this project, there are two types of performance analyses will be conducted. The first performance analysis is the qualitative analysis. This qualitative analysis is carried out by evaluating the quality of mammograms visually. The second performance analysis is the quantitative analysis. Instead of using human eye, the mammograms are analyzed by using appropriate statistical methods and certain quantitative values will be evaluated.

2.5.1 Qualitative Analysis

The qualitative analysis is one of the performance analyses that can be performed to evaluate the performance of the adopted techniques. In qualitative analysis, the mammograms that produced by the adopted techniques are observed using human eye and evaluate it in term of the contrast, amount of the detail revealed and overall brightness of the mammograms. The result of this qualitative analysis is solely based on the perception of human eye on the resultant images produced and there are no numerical results involved. Result for this qualitative analysis is subjective and observer dependant. This is because different observer will have different perception on the resultant mammogram that produced by the adopted technique. Besides that, the environments where the observers perform qualitative analysis will affect the judgment of observers. However, an adopted technique will be considered to have excellent performance and capability if the mammogram produced has enhanced contrast, enhanced brightness and high amount of detail revealed.

2.5.2 Quantitative Analysis

In order to further evaluate the capability and the performance of the adopted fuzzy image enhancement technique, quantitative analysis is employed. In the quantitative analysis, several tests will be performed to evaluate the quality of mammogram that enhanced by adopted techniques. The quality of mammogram produced can be evaluated in term of images' brightness, contrast and amount of information revealed. Each of the tests in quantitative analysis will produce numerical results that indicate the degree of improvement observed on the output mammogram after applying the adopted techniques.

According to Singh and Bovis (2005), the distributions of target *T* and background *B* can be plotted as two normal Probability Density Functions (PDF's) with mean $\mu_B{}^O$, $\mu_T{}^O$ and standard deviations $\sigma_B{}^O$, $\sigma_T{}^O$ respectively as shown in Figure 2.4 for an original image *O*.

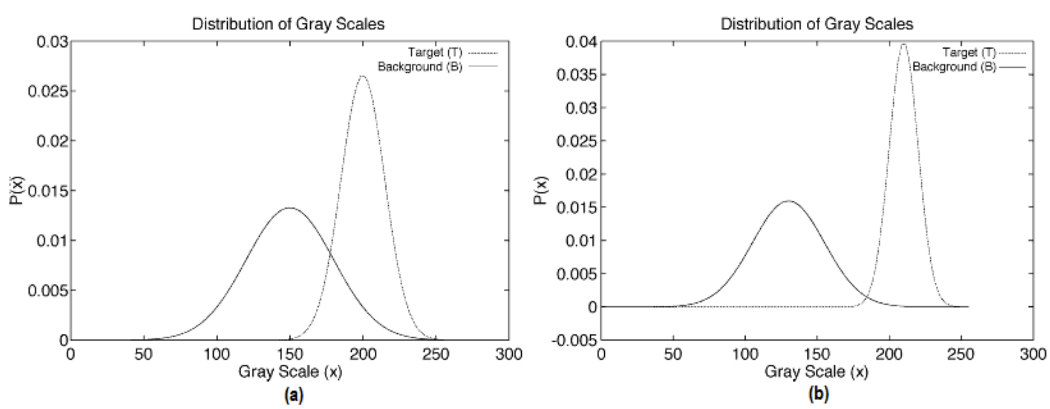

Figure 2.4: Distribution overlap between background B and target T (a) before enhancement and (b) after enhancement. Adopted from Singh & Bovis (2005).

Typically there is an overlap between the two distributions, within which confusion occurs over pixels/distribution membership. The aim of any enhancement technique should be to maximize the distance between these two distributions thus ensuring that the target is visible against the background. Using this observation, a measure of the separation between these two PDF's would be an indicator of the performance of the enhancement technique. Following the application of the enhancement technique and the generation of the enhanced image *E*, the two distributions for *B* and *T* with mean μ_B^E, μ_T^E and standard deviation σ_B^E *and* σ_B^T are evaluated. In this study, three tests used are Distribution Separation Measure (DSM), Target-to-Background Contrast Enhancement Measurement Based on Standard Deviation (TBCs) and Target-to-Background Contrast Enhancement Measurement Based on Entropy.

a. Distribution Separation Measure (DSM)

The first quantitative test used is the Distribution Separation Measure (DSM). The DSM is the distance measure between the decision boundaries and the means of the targets and background, before and after segmentation (Singh & Bovis, 2005). This is defined in Eq. (2.4) as:

$$\text{DSM} = \left(\left|\mu_T{}^E - \mu_B{}^E\right|\right) - \left(\left|\mu_T{}^O - \mu_B{}^O\right|\right) \qquad (2.4)$$

where $\mu_T{}^O$ and $\mu_B{}^O$ are the mean of the grayscales comprising the background and target area, respectively, of the original image before enhancement while $\mu_T{}^E$ and $\mu_B{}^E$ are the mean of the grayscales comprising the background and target area, respectively, of the enhanced image. Ideally, the measurement should be greater than zero; the greater the DSM value, the better the performance of the fuzzy image enhancement technique.

b. Target-to-Background Contrast Enhancement Measurement Based on Standard Deviation (TBCs)

The Target-to-Background Contrast Enhancement Measurement Based on Standard Deviation (TBCs) test is the second quantitative analysis that is used to evaluate the performance of adopted techniques. According to Singh & Bovis, the key objective of a contrast enhancement is to maximize the difference between the background and target mean grey scale level and ensure that the homogeneity of the MCs is increased aiding the visualization of its boundaries and location. Using the ratio of the standard deviation of the grayscales within the target before and after the enhancement, the improvement can be quantified using the given in Eq. (2.5).

$$\text{TBCs} = \frac{\left(\dfrac{\mu_T{}^E}{\mu_B{}^E}\right) - \left(\dfrac{\mu_T{}^O}{\mu_B{}^O}\right)}{\dfrac{\sigma_T{}^E}{\sigma_T{}^O}} \qquad (2.5)$$

Where $\mu_T{}^E$, $\mu_B{}^E$, $\mu_T{}^O$, $\mu_B{}^O$ are the mean of the grey scales comprising the target and background respectively of the original image before and after enhancement and where $\sigma_T{}^E$, $\sigma_T{}^O$ are the standard deviations of the grey scales before and after enhancement. The target has a greater density within the mammogram thus having higher value of mean grey scale intensity compared to the surrounding background. For a good enhancement technique, the value of TBCs is larger. This is because the good enhancement technique can enhance the contrast between target and background by increasing the mean grey scale of the target area while reducing the mean grey of the background area. Typical values for TBCs will range between -∞ through to +∞.

c. Target-to-Background Contrast Enhancement Measurement Based on Entropy (TBCε)

Besides that, the background contrast ratio can also be calculated using the entropy ε of target and background areas within an image. The calculation for this measure is in similar manner to TBCs by determining the difference between ratios of the mean grey scales in the target and background areas in both original and enhanced images as (Hassanien *et al.*, 2004):

$$\text{TBC}\varepsilon = \frac{\left(\dfrac{\mu_T{}^E}{\mu_B{}^E}\right) - \left(\dfrac{\mu_T{}^O}{\mu_B{}^O}\right)}{\dfrac{\varepsilon_T{}^E}{\varepsilon_T{}^O}} \qquad (2.6)$$

Where $\varepsilon_T{}^E$ and $\varepsilon_T{}^O$ are the entropy of the target in the original and enhancement image, respectively. An effective enhancement technique will lead to a large value of TBCε. Typical values for TBCs will range between -∞ through to +∞.

2.6 Summary

Nowadays, breast cancer has become the most common cancer in women in most parts of the world. Since early detection is the best defensive line against the breast cancer, hence mammography is playing very important role. Due to the fuzzy nature of the mammogram and the low contrast between the breast cancer and its surroundings, these cause difficulty for radiologist in interpretation of mammogram and this is the reason why the contrast enhancement will be our main focus in this chapter.

Throughout this chapter, the details on mammogram image enhancement and the reviews for previous enhancement techniques that been applied on mammogram has been discussed. Besides that, the conventional image enhancement techniques and also the fuzzy image enhancement techniques also been introduced. In order to evaluate the performance of the fuzzy image enhancement techniques, two types of performance analysis called qualitative analysis and quantitative analysis are employed. For qualitative analysis, the mammogram produced by the fuzzy image enhancement techniques will be observed based on the perception of observer. On the other hand, quantitative analysis uses statistical methods to examine the capability of adopted techniques. A total of three analyses are suggested, namely Distribution Separation Measure (DSM), Target-to-Background Contrast Enhancement Measurement Based on Standard Deviation (TBCs) and Target-to-Background Contrast Enhancement Measurement Based on Entropy (TBCε). In the next chapter, the methodology of the whole project implementation will be discussed in details.

CHAPTER 3
METHODOLOGY

3.1 Introduction

Many difficulties in image processing arise because of the uncertainty that exists on mammogram. Due to this uncertainty likes imprecise borders, defined shapes and different densities and texture, mammogram are inherently "fuzzy" and it is believe that fuzzy set theory is a useful tool for handling the uncertainty associated with vagueness and imprecision. Therefore, several fuzzy image enhancement techniques have been adopted in this study to improve the quality of the mammogram and generally provide the clearer image for a human observer and it can also form a pre-processing step for subsequent automated analysis. Following this chapter, the methodology of this study will be discussed in detail.

3.2 Project Implementation

Basically, the project implementation consists of three phases as illustrated in Figure 3.1. There are image pre-processing, implementations of fuzzy image enhancement techniques and the last is performance analysis on the output image. The details for each phase will be discussed in the following sections.

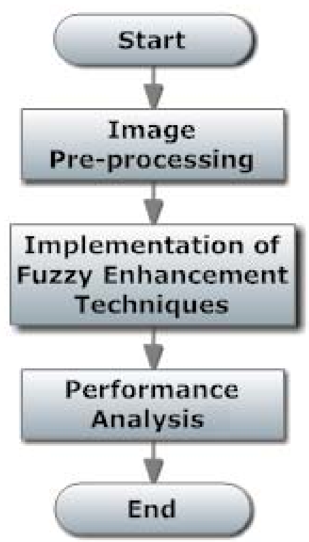

Figure 3.1: The flow chart for project implementation.

3.2.1 Image Pre-processing

As mentioned in previous chapters, some problems are encounted in mammography interpretation especially in MCs detection. The reasons and the problems are listed as below:

1. MCs are very small (may smaller than 0.1 mm until cannot be distinguished in the film-screen mammography from the high-frequency noise).
2. MCs may be low contrast so that the intensity difference between suspicious areas and their surrounding tissues can be quite slim.

Hence, this phase is mainly focus on high-frequency noise removal and contrast enhancement to solve the questions that mentioned above and the detail portion of image pre-processing of Figure 3.1 is illustrated in Figure 3.2.

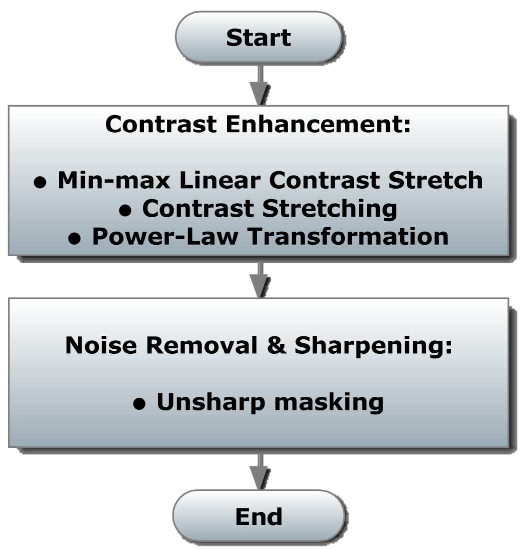

Figure 3.2: The flow chart for phase 1 (image pre-processing).

As illustrated in Figure 3.2, image pre-processing contains two main steps. They first step is contrast enhancement and the second step is noise removal and sharpening. There are three conventional image enhancement techniques used in contrast enhancement process and more detail explanation for the process is illustrated in the Figure 3.3.

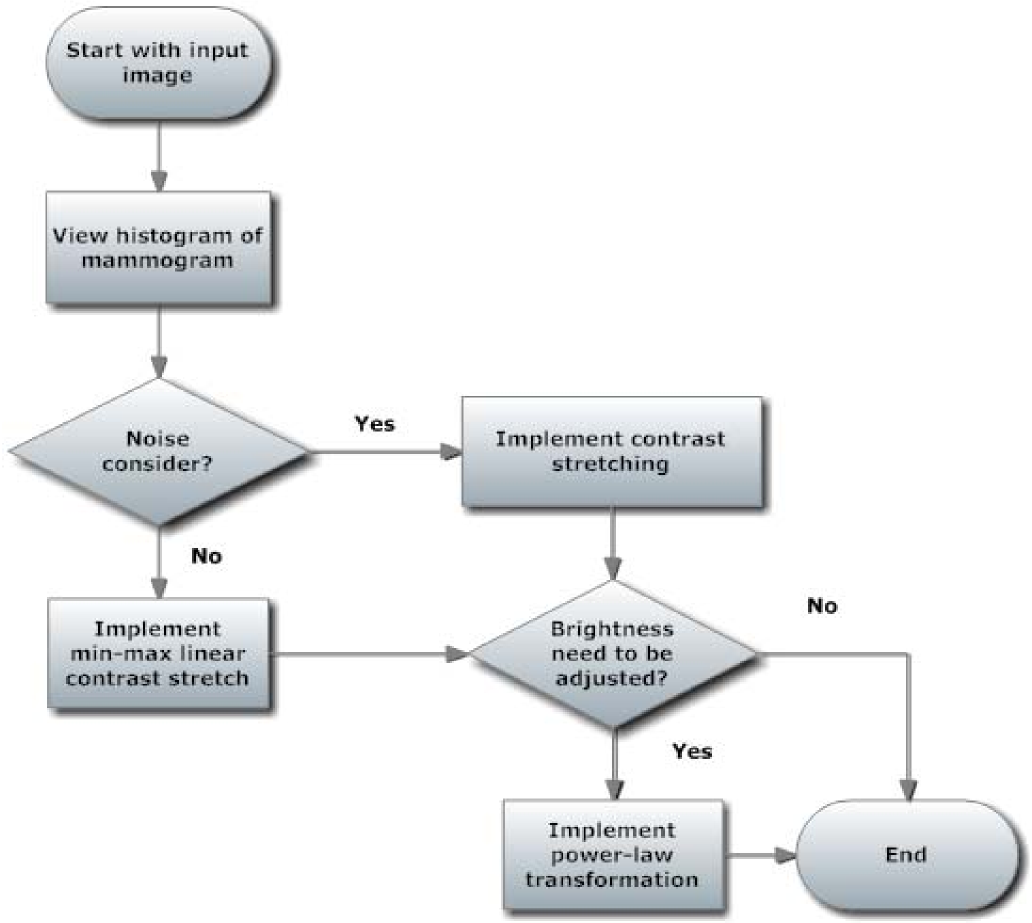

Figure 3.3: The flow of step 1 (contrast enhancement) in image pre-processing.

As illustrated in Figure 3.3, the histogram of the original mammogram is viewed first to inspect either impulse noise is appear on mammogram or not. If the mammogram is free of impulse noise, min-max contrast stretch is used to enhance the contrast of mammogram by assigning the original minimum and maximum values of the data to a newly specified set of values that utilize the full range of available brightness values and the implementation is follow Eq. (2.2).

If the noise is taken into consideration, contrast stretch should be used because the impulse noise on the mammogram will affect the performance of min-max linear contrast stretch technique since the technique relies on the minimum and maximum gray level of the mammogram. This impulse noise will affect the extreme values used in the scaling of the output mammogram. Hence, user can determine the minimum and maximum gray level of the mammogram as threshold in the computation. To stretch the contrast, the histogram is scanned from the lowest pixel value upward and from the highest pixel value downward to find the first pixel that exceeds a certain threshold.

Sometimes, the intensity of gray level of mammogram is modify for better illustration. Hence, power-law transformation that mentioned in Section 2.21 can be used. Follow the Eq. (2.1), intensity of the gray level can be adjusted by using power-law curves with suitable fractional exponent values of γ that map a narrow range of dark input values into a wider range of output values, with the opposite being true for higher values of input levels.

Next, the contrast enhanced mammogram will be the input to unsharp masking process for the purpose of image smoothing, noise removal and image sharpening. The unsharp filter is the mask that obtained by subtracting the smooth version of image from the original and it used as simple sharpening operator to enhances edges. Basically, the implementations of unsharp masking are illustrated in Figure 3.4.

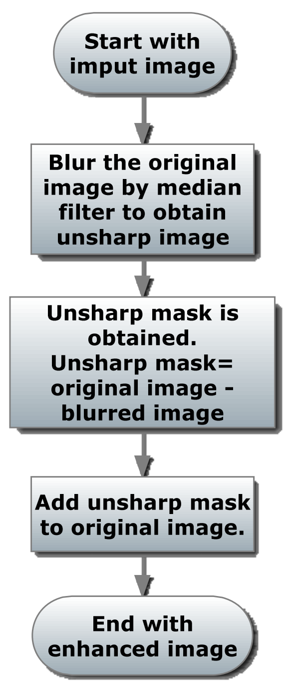

Figure 3.4: The unsharp masking process.

3.2.2 Implementation of Fuzzy Enhancement Techniques

To implement fuzzy image enhancement, the grayscale of an image is mapped onto a fuzzy plane using certain membership transformation function. In other words, each pixel on an image plane can be mapped to a fuzzy plane by using a certain fuzzy transformation function. Mapping process is necessary to increase the contrast of an image by giving a larger weight to the gray levels that are closer to the mean gray level of an image than those that are farther from the mean. In this study, total of four fuzzy image enhancement techniques with different fuzzy transformation function are used and being investigated, they are:

1. Contrast Improvement with Fuzzy Histogram Hyperbolization (FHH)
2. Contrast Improvement with Intensification Operator (INT)
3. Contrast Improvement based on Fuzzy if-then Rules (FIT)
4. Contrast Improvement with Possibility Distribution (PD)

The enhanced image that resulted from phase 1 will become the input for one of the fuzzy image enhancement techniques. As reviewed in section 2.3, each fuzzy image enhancement technique has the general structure that illustrated in Figure 3.5 and the difference for each technique is just the knowledge that applied in membership modification. In the next, the implementation for each fuzzy image enhancement technique is discussed in details.

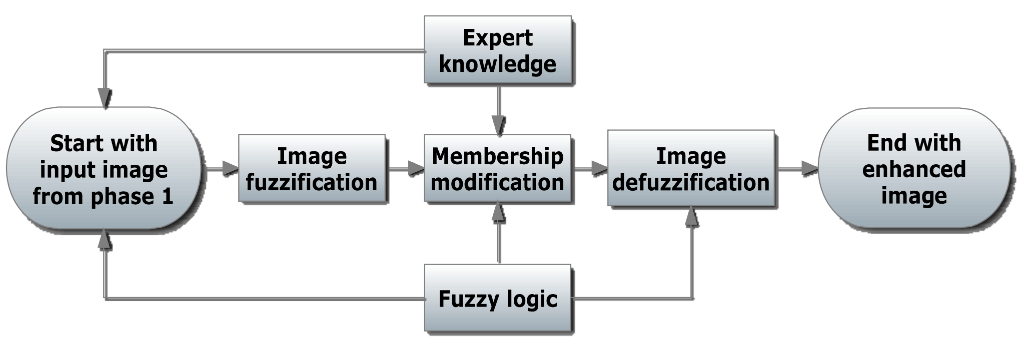

Figure 3.5: General structure of fuzzy image enhancement technique