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## COMPUTER-AIDED DETECTION OF BREAST CANCER USING ULTRASOUND

#### IMAGES

by

## Yanhui Guo

## A dissertation submitted in partial fulfillment of the requirements for the degree

of

## DOCTOR OF PHILOSOPHY

in

**Computer Science** 

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2010

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#### ABSTRACT

#### Computer-Aided Detection of Breast Cancer Using Ultrasound Images

by

Yanhui Guo, Doctor of Philosophy

Utah State University, 2010

Major Professor: Dr. Heng-Da Cheng Department: Computer Science

Ultrasound imaging suffers from severe speckle noise. We propose a novel approach for speckle reduction using 2D homogeneity and directional average filters to remove speckle noise. We transform speckle noise into additive noise using a logarithm transformation. Texture information is employed to describe the speckle characteristics of the image. The homogeneity value is defined using texture information value, and the ultrasound image is transformed into a homogeneity domain from the gray domain. If the homogeneity value is high, the region is homogenous and has less speckle noise. Otherwise, the region is nonhomogenous, and speckle noise occurs. The threshold value is employed to distinguish homogenous regions from regions with speckle noise obtained from a 2D homogeneity histogram according to the maximal entropy principle. A new directional filtering is convoluted to remove noise from pixels in a nonhomogenous region. The filtering processing iterates until the breast ultrasound image is homogenous enough. Experiments show the proposed method improves denoising and edge-preserving capability. We present a novel enhancement algorithm based on fuzzy logic to enhance the fine details of ultrasound image features, while avoiding noise amplification and overenhancement. We take into account both the fuzzy nature of an ultrasound and feature regions on images, which are significant in diagnosis. The maximal entropy principle utilizes the gray-level information to map the image into fuzzy domain. Edge and textural information is extracted in fuzzy domain to describe the features of lesions. The contrast ratio is computed and modified by the local information. Finally, the defuzzification operation transforms the enhanced ultrasound images back to the spatial domain. Experimental results confirm a high enhancement performance including fine details of lesions, without over- or under-enhancement.

Identifying object boundaries in ultrasound images is a difficult task. We present a novel automatic segmentation algorithm based on characteristics of breast tissue and eliminating particle swarm optimization (EPSO) clustering analysis, thus transforming the segmentation problem into clustering analysis. Mammary gland characteristics in ultrasound images are utilized, and a step-down threshold technique is employed to locate the mammary gland area. Experimental results demonstrate that the proposed approach increases clustering speed and segments the mass from tissue background with high accuracy.

(130 pages)

This work is dedicated to my family,

especially to my wife, Xiaolei Meng.

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#### CHAPTER 1

#### **INTRODUCTION**

#### **1.1 Cancer and Breast Cancer**

One in eight deaths worldwide is due to cancer [1]. Cancer is the second leading cause of death in developed countries and the third leading cause of death in developing countries. In 2009, about 562,340 Americans died of cancer, more than 1,500 people a day. Approximately 1,479,350 new cancer cases were diagnosed in 2009. In the United Sates, cancer is the second most common cause of death, and accounts for nearly 1 of every 4 deaths [2].

Breast cancer is the most common, life-threatening cancer among American women[3]. The chance of developing invasive breast cancer at some time in a woman's life is about 1 in 8 (12%) [4, 5]. Breast cancer continues to be a significant public health problem in the world. Approximately 182,000 new cases of breast cancer are diagnosed and 46,000 women die of breast cancer each year in the United States [6]. In 2009, 192,370 new cases of invasive breast cancer were diagnosed among women in the United States [3]. Thus, the incidence and mortality of breast cancer are very high, so much so that breast cancer is the second leading cause of cancer death in women. The chance that breast cancer will be responsible for a woman's death is about 1 in 35 (about 3%) [4]. In 2009, about 40,610 women died from breast cancer in the United States [7].

Although breast cancer has very high incidence and death rate, the cause of breast cancer is still unknown [4]. No effective way to prevent the occurrence of breast cancer exists. Therefore, early detection is the first crucial step towards treating breast cancer. It plays a key role in breast cancer diagnosis and treatment.

#### **1.2 Breast Cancer Detection Methods**

Breast cancer screening is vital to detecting breast cancer. The most common screening methods are mammography and sonography. Of these, mammography is probably the most important tool that doctors use to detect, diagnose, and evaluate breast cancer. A mammogram is an x-ray photograph of the breast. This technique has been in use for about 40 years [8] and is the current "gold standard" for diagnosing breast disease. It can reveal breast cancer even when the lump is very small and not palpable. In fact, various studies have shown that undergoing regular mammography examinations can save lives [6].

However, mammography still has some disadvantages for breast cancer detection. While it is very sensitive, it is not accurate in detecting breast cancer [9]. As a result, approximately 65% of cases referred to surgical biopsy are actually benign lesions [10, 11]. Mammography also has limitations in cancer detection in the dense breast tissue of young patients. Most cancers arise in dense tissue, so lesion detection for women in this higher risk category is particularly challenging. The breast tissue of younger women tends to be dense and full of milk glands, making cancer detection with mammography problematic. In mammograms, glandular tissues look dense and white, much like cancerous tumors [12]. Furthermore, mammography can identify an abnormality that looks like a cancer, but turns out to be normal. Called a false positive, such a misdiagnosis means more tests and diagnostic procedures, which is stressful for patients. To make up for these limitations, more than mammography is often needed for sound diagnosis [13]. Moreover, reading mammograms is a demanding job for radiologists. An accurate diagnosis depends on training, experience, and other subjective criteria. About 10 percent of breast cancers are missed by radiologists, and most of these are in dense breasts [14]. On the other hand, about two-thirds of the lesions that are sent for biopsy are benign. The reasons for this high miss rate and low specificity in mammography are the following: the low conspicuity of mammographic lesions, the noisy nature of the images, and the overlying and underlying structures that obscure features of a region of interest (ROI) [15].

Sonography is an important adjunct to mammography to identify, characterize, and localize breast lesions, and it has the added advantage of not being limited by dense breasts. It also has no radiation or compression [16]. Consequently, sonography is more effective for women younger than 35 years of age [17]. Thus, it has proven to be an important adjunct to mammography in breast cancer detection and useful for differentiating cysts from solid tumors. Furthermore, it has been shown that breast sonography is superior to mammography in its ability to detect local abnormalities in the dense breasts of adolescent women [18]. Results [19] suggest that the denser the breast parenchyma, the higher the detection accuracy of malignant tumors using ultrasound. The accuracy rate of breast ultrasound has been reported to be 96-100% in the diagnosis of simple benign cysts [20]. Breast ultrasound examination is playing an increasingly significant role in detecting breast cancers, due to the fact that sonography can reveal a mass otherwise obscured mammgraphically by dense tissue, it is low cost, portable, and requires no ionizing radiation [21]. As a result of these advantages, ultrasound imaging is more suitable to large-scale screening and diagnosis.

Sonography [22] uses high frequency broadband sound waves in the megahertz range that are reflected by tissue to varying degrees to produce images. Ultrasound is a gray-scale display of the area being imaged and is used in imaging abdominal organs, heart, breast, muscles, tendons, arteries and veins. It can study the function of moving structures in real-time and has no ionizing radiation. As well as being very safe to use, it is relatively inexpensive and quick to perform. The real time moving image obtained can be used to guide drainage and biopsy procedures. In short, ultrasound imaging is noninvasive, practically harmless, and cost effective for diagnosis, and it has become one of the most prevalent and effective medical imaging technologies [23].

A breast ultrasound is an imaging technique that sends high-frequency sound waves through breast tissues and converts them into images on a viewing screen. The ultrasound examination places a sound-emitting probe on the breast to conduct the test. There is no radiation involved. Ultrasound is the best way to find out if the abnormality in breast is solid (such as a benign fibroadenoma or cancer) or fluid-filled (such as a benign cyst) [12].

In the last two decades, breast ultrasound images has become an adjunct to mammography to help differentiate benign from malignant lesions [24]. Its benefits of safety and cost-effectiveness discussed above [25] have moved ultrasound ultrasound techniques into an increasingly important role in the evaluation of breast lesions [26]. Like ultrasound exams in general, breast ultrasound exams are relatively inexpensive and do not use X-rays or other types of potentially harmful radiation. They can differentiate between solid and cystic breast masses, help to define the nature and extent of a mass, and show all areas of the breast, including the area closest to the chest wall, which can be difficult to study with a mammogram. Consequently, breast examination using ultrasound technology has become a major adjunct to mammography. Compared to mammography, breast ultrasound examinations have several advantages [19]:

1. Breast ultrasound examinations can obtain any section image of breast, and observe the breast tissues in real-time and dynamically.

2. Ultrasound imaging can depict small, early-stage malignancies of dense breasts, which is difficult for mammography to achieve.

3. Sonographic equipment is portable and relatively cheap, and has no ionizing radiation and side effects.

Several statistical studies on the accuracy rate of breast disease diagnosis using ultrasonic examination have been carried out [27, 28] (see Table 1.1). As demonstrated in Table 1.1, ultrasound examination has a high detection rate of tumors, in particular of malignant tumors.

However, the ultrasound image itself has some limitations, such as low resolution and low contrast, speckle noise, and blurry edges between various organs, so it is more difficult for a radiologist to read and interpret an ultrasound image. In addition, ultrasound diagnosis is heavily dependent on a doctor's personal experience. This reality is compounded by the fact that reading an ultrasound image is tedious, hard work, which can lead to fatigue and burn out, which, in turn, can ultimately lead to an increased rate of misdiagnosis and missed diagnosis. Therefore, using digital image processing and pattern

Туре	Ultrasound Detection Accuracy	
Benign	84.5%	
hyperplasia	<b>7</b> 0.00/	
Benign tumor	79.0%	
Malignant	88.5%	
tumor	00.070	

Table 1.1. Accuracy Rate of Breast Disease DiagnosisUsing Ultrasonic Examination.

recognition techniques to deal with ultrasound imaging in general and to apply these techniques to clinical breast cancer detection is of critical importance.

#### **1.3 Computer-aided Detection**

#### 1.3.1 Introduction of Computer-aided Detection

In order to increase detection and diagnosis accuracy and save to labor, computeraided detection (CAD) systems have been developed to help radiologists to evaluate medical images and detect lesions at an early stage. In general, CAD is a procedure that employs computers to assist doctors in the interpretation of medical images [22]. A CAD system is an interdisciplinary technology combining elements of digital image processing with radiological image processing. It combines image processing techniques and experts' knowledge for greatly improved accuracy of abnormality detection. In particular, the CAD system for automated detection/classification of masses and microclassification of clusters can be very useful for breast cancer control. CAD systems can provide doctors a "second pair of eyes," whose consistency and repeatability is very good, thus greatly reducing the false negative rate and improving the true positive rate.

#### 1.3.2 Introduction of Breast Cancer Computer-aided Detection

A typical CAD application is the detection of tumors in a breast ultrasound image. Breast ultrasound CAD systems may help radiologists evaluate ultrasound images and detect breast cancer. Such systems are used in addition to the human evaluation of the diagnosis. A breast ultrasound CAD system not only improves the ultrasound image quality, increases the image contrast, and automatically determines lesion location, and it also greatly reduces the human workload associated with the diagnosis, and improves the accuracy of detection and diagnosis.

Generally, a typical breast ultrasound CAD system includes three steps:

- 1. Ultrasound image acquisition
- 2. Ultrasound image preprocessing
  - a. Speckle reduction to suppress noise
  - b. Enhancement to improve the contrast of the image
- 3. Ultrasound image segmentation, i.e., locating suspicious regions within the digitized ultrasound image.

The structure of a breast ultrasound CAD system is shown in Figure 1.1.



Figure 1.1. Breast ultrasound CAD system.

## 1.4 Methods of Breast Cancer Computer-aided Detection

Because of an ultrasound's attenuation characteristics, identical textures at different depths have a different brightness, and the images are further corrupted by speckle noise. Therefore, the first step in breast ultrasound image CAD system is preprocessing that suppresses the speckle noise.

The underlying principles behind preprocessing are to make an image clearer and to improve the contrast of the image. The purpose of the enhancement of a breast ultrasound image is to produce a reliable representation of breast tissue structures by enhancing the contrast and suppressing the noise in image. An effective method for enhancement must be able to enhance the texture and features of masses for the following reasons: (1) the low-contrast of breast ultrasound images; and (2) the typically hard-toread masses in breast ultrasound images. The ideal contrast enhancement approach should have neither over-enhancement nor under-enhancement. To address issues that arise in preprocessing, this research developed a novel contrast enhancement algorithm based on both local and global information.

A breast cancer CAD scheme separates suspicious regions that may contain masses from the background parenchyma – the tissue characteristic of an organ, as distinguished from associated connective or supporting tissues. In other words, such schemes partition the mammogram into several nonintersecting regions and extract regions of interest (ROIs) and suspicious mass candidates from the ultrasound image. While a suspicious area is darker than its surroundings, it has a similar density, a regular shape of variable size, and fuzzy boundaries, often making a distinction between the area and its surroundings difficult. Thus, image segmentation is essential to maintaining the sensitivity and accuracy of the entire mass detection and classification system.

Generally, a breast CAD system uses some image processing methods: image denoising, image enhancement and image segmentation.

#### 1.4.1 Image Denoising

Digital images play an important role both in daily life applications, such as satellite television, magnetic resonance imaging, and computer tomography, as well as in areas of research and technology, such as geographical information systems and astronomy [29]. Image noise is generally regarded as an undesirable byproduct of the image capture. Image data are generally contaminated by noise. Noise occurs in images for many reasons including imperfect instruments, problems with the data acquisition process, and interfering natural phenomena. Furthermore, noise can be introduced by transmission errors and compression. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Consequently, denoising is often a necessary and, thus, is typically the first step taken before the image data are analyzed. However, image denoising still remains a challenge for researchers because noise removal introduces artifacts into the image and causes blurring.

Generally, image noise includes Gaussian noise, salt and pepper noise, and speckle noise. The noise in the image can be categorized into two groups: additive and multiplicative models [30].

Let  $f(\cdot)$  denote an image. We decompose the image into a desired component,  $g(\cdot)$ , and a noise component,  $q(\cdot)$ . The most common decomposition is additive:

$$f(\cdot) = g(\cdot) + q(\cdot) \tag{1.1}$$

For instance, Gaussian noise is usually considered to be an additive component.

The second most common decomposition is multiplicative:

$$f(\cdot) = g(\cdot)q(\cdot) \tag{1.2}$$

An example of a noise often modeled as multiplicative is speckle noise.

Ultrasound imaging uses low-power, high frequency sound waves to visualize the body's internal structures and creates pictures of tissues and organs [31]. As the sound waves pass through a body, they are reflected back to the ultrasound machine in different ways, depending on the characteristics of the tissues encountered. As stated previously, among the currently available medical imaging techniques, ultrasound (US) imaging is regarded as a noninvasive, practically harmless, portable, accurate, and cost effective method for diagnosis [32]. These properties make US imaging the most prevalent diagnostic tool in used in hospitals around the world.

Unfortunately, the quality (resolution and contrast) of ultrasound image is generally degraded due to the existence of special noise, called speckle for short [32-36]. Speckle is caused by interference effects of echoes from unresolved random scatters due to the coherent nature of ultrasound scanners [33]. It occurs when a coherent source and a noncoherent detector are used to interrogate a medium whose surface is rough on the scale of a typical ultrasound wavelength. Speckle noise occurs in the images of soft organs, such as the liver and kidney, whose underlying structures are too small to be resolved by the large wavelength ultrasound uses. Speckle noise degrades image quality, and it makes tlow-contrast objects, small high-contrast targets, and small differences hard to be detected [33]. Speckle noise can significantly degrade image quality and increase difficulties in diagnosis. Therefore, it is important to improve image quality of tissue structures by reducing speckle noise.

Speckle reduction techniques are classified into three groups [34]: filtering techniques, wavelet domain techniques, and compounding approaches. Speckle reduction techniques are summarized in detail in [34].

#### 1.4.2 Image Enhancement

Image enhancement is another important step in image preprocessing techniques. The underlying principle of this step is to make the image clearer. Image enhancement improves the quality (clarity) of images for human viewing. Increasing contrast and revealing details are important tasks of enhancement operations. The goal of all image enhancement is to produce a processed image that is suitable for a given application [35]. An image might be required to be easily inspected by a human observer or be analyzed and interpreted by a computer. For example, suppose there is a cell in an image that is of low contrast and somewhat blurry. Increasing the contrast range could enhance the image. The original image might have areas of very high and very low intensity, which mask details. The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide "better" input for other automated image processing techniques [36].

Image enhancement is one of the most important issues in low-level image processing. Its purpose is to improve the quality of low contrast images and to correct deficiencies of the contrast. Therefore, the underlying principle of the enhancement is to enlarge the intensity difference among objects or between the pixel and its neighbors with the condition that the image itself is not distorted.

Image enhancement techniques can be divided into two broad categories [35, 36]: spatial domain methods, which operate directly on pixels, and frequency domain methods, which operate on the Fourier transform of an image. In this dissertation, we primarily discuss the spatial domain methods. The enhancement methods in the spatial domain are classified as global modification approaches and local processing approaches. The ideal contrast enhancement approach should have neither over-enhancement nor underenhancement.

Generally, global methods are implemented by using histogram modification. One of the most useful global methods is histogram equalization (HE). The central idea of

HE-based methods is to reassign the intensity values of pixels in order to make the new distribution of intensities uniform to the utmost extent [37-40]. In contrast enhancement techniques, which are often based on HE [37], the pixel values in the image are altered to make the distribution of gray level values as uniform as possible. HE can enhance the overall visibility of an image, but they can neither increase nor decrease the local contrast at some local positions in the image. If this were to occur, a lot of detailed information in the image would be ignored. HE is simple and effective in enhancing an entire low-contrast image containing only single object or no apparent contrast change between the object and the background. Otherwise, it does not work well. It is also not effective in texture enhancement.

The authors of [38] proposed a variation of histogram equalization known as adaptive histogram equalization (AHE), or local area histogram equalization (LHE), that uses a sliding subblock to define an image region for each pixel. The histogram of the region is then equalized to determine the output value for the pixel. The LHE procedure is computationally intensive because a separate histogram is constructed for each image pixel. Dale-Jones [39] modified LHE by varying the window size over different regions of the image in order to enhance each region equally. Although LHE makes more detail in the image visible, it is still unsuitable for medical ultrasound image processing due to the computational complexity and background distortion.

Local methods are very effective in image contrast enhancement, and their implementation can employ feature-based approaches such that local features are obtained by edge detecting operators or local statistic information such as local mean, standard deviation, etc. There are many methods that implement contrast enhancement by modifying tpixel features [40-44]. The common feature-based method is to define the contrast ratio first, and then enhance the image contrast by increasing the contrast ratio. Another way is based on local histogram modification. It uses histogram modification to enhance the image contrast in a local area of the image [45-49], such as local histogram equalization, local histogram stretching, and nonlinear mapping methods (square, exponential, and logarithmic function). The main idea is to define a local function for each pixel based on the pixels within a small window centered at the pixel. These methods are quite effective in local texture enhancement. However, most of these local methods make no contribution to the enhancement of the entire image. To a certain extent, the image is distorted since the transformation is not a monotonic mapping and the order of gray levels of the original image could be changed.

It is well known that breast ultrasound images have low contrast and some degree of fuzziness, such as indistinct cyst borders, ill-defined mass shapes, and different tumor densities, which make it hard to read masses in an image. Therefore, it is necessary to employ image enhancement techniques to improve contrast in breast ultrasound images. The overarching purpose of ultrasound image enhancement is to increase the visibility of the image by enlarging the contrast between the object and background so that more image details can be discerned [50]. The processed breast ultrasound image should produce reliable representations of breast tissue structures by enhancing the contrast. Any effective method for enhancement must enhance texture and features of masses for doctors to make a diagnosis.

#### 1.4.3 Image Segmentation

Image segmentation is a critical technique in image processing. As such, it serves

as an important stepping stone towards pattern detection and recognition, which determines the quality of the final image analysis. Image segmentation is used to extract the meaningful objects from the image [51]. Moreover, it plays an important role in a variety of applications such as robot vision, object recognition, and medical imaging. In [52], Spirkovska defines image segmentation as a bridge between a low level vision subsystem and a high level vision subsystem.

To understand an image, one needs to isolate the objects in it and find relationships among them [51]. Image segmentation divides an image into several segments wherein each segment is visually coherent. Thus, image segmentation can be defined as a process that divides an image into different regions such that each region is homogeneous, but the union of any two adjacent regions is not homogeneous; i.e., it is a partition of image *I* into non-overlapping regions  $S_i$  [53]:  $\bigcup S_i = I$  and  $S_i \cap S_j = \phi$ ,  $i \neq j$ .

While it markedly influences the final result of the analysis, image segmentation is one of the most difficult tasks within the broader image processing field. Because many features such as intensity, blurring, contrast, and even the number of segments affect the quality of segmentation, it is not easy to extract all meaningful objects correctly and precisely from an image without any human interaction or supervision [54].

Several segmentation approaches have been proposed. Gray image segmentation approaches are based on either discontinuity and/or homogeneity of gray level values in a region. Discontinuity-based approaches tend to partition an image by detecting isolated points, lines, and edges according to abrupt changes in gray levels. Other segmentation methods include [53] edge-based methods, threshold methods, region-based methods and clustering-based methods. Image segmentation is the second stage of mass detection using CAD schemes, which separating suspicious regions that may contain masses from background parenchyma, i.e., partitioning the breast ultrasound image into several non-intersecting regions, and extracting ROIs and suspicious mass candidates from the ultrasound image. A suspicious area is an area that is darker than its surroundings, has almost the same density, has a regular shape with varying size, and has fuzzy boundaries. This is a very essential and important step that determines the sensitivity of the entire system. Segmentation methods do not need to be exacting in finding mass locations, but the result for segmentation should include regions containing all masses. The goal for segmentation is to obtain the suspicious areas to assist radiologists in diagnosis [34]. The result of a good segmentation depends on a suitable algorithm for specific features. According to their natures, there are four kinds of breast ultrasound image segmentation techniques [34, 55], histogram thresholding, active contour model, Markov random field, and neural network methods. Segmentation techniques are summarized in [34, 55].

This research focuses on developing a novel CAD system for the automatic detection of masses in breast ultrasound images. The rest of this dissertation is organized as follows. Chapter 2 discusses a novel speckle reduction method to remove the noise on the breast ultrasound images. Chapter 3 discusses a novel automatic enhancement approach to increase the contrast of the breast ultrasound images. Chapter 4 presents the adaptation of the particle swarm optimization and clustering analysis algorithm for segmenting the suspicious areas from the background. Finally, Chapter 5 gives conclusions and directions for future work.

#### CHAPTER 2

#### SPECKLE REDUCTION ON ULTRASOUND IMAGES

Ultrasound medical imaging uses low-power, high frequency sound waves to visualize the body's internal structures and create pictures of tissues and organs [31]. As the sound waves pass through a body, they are reflected back to the ultrasound machine in different ways, depending on the characteristics of the tissues encountered. Among the currently available medical imaging techniques, ultrasound (US) imaging is regarded as a noninvasive, practically harmless, portable, accurate, and cost effective method for diagnosis [32]. These properties make US imaging the most prevalent diagnostic tool in nearly all hospitals around the world.

Unfortunately, the quality, i.e., resolution and contrast, of ultrasound imaging is generally limited by noise, also called speckle [32, 56-59]. Speckle noise occurs when a coherent source and a noncoherent detector are used to interrogate a medium, whose surface is rough on the scale of a typical ultrasound wavelength. Especially, speckle noise occurs in the images of soft organs such as the liver and kidney whose underlying structures are too small to be resolved by the large wavelengths used in ultrasound. Speckle noise can significantly degrade image quality and thus increase difficulties in diagnosis.

#### 2.1 Summary of Speckle Reduction Methods

#### 2.1.1 Filtering Methods

Several filters have been proposed for reducing speckle noise: linear filters [56, 57, 60], temporal averaging [57, 61], and median filter [62, 63]. The method proposed in

[64] combines a series of nonlinear filters for speckle reduction. The authors state that the combination of averaging and nonlinear Gaussian filtering improves image quality. However, the method is developed mainly for additive random noise reduction and has little success in speckle suppression. The authors of [65] report that the linear filtering is far from being an optimal tool for suppressing speckle noise because it tends to reduce noise at the expense of overly smoothing the image. Additionally, the image further suffers from the loss of important details, such as small vessels and texture patterns, due to blurring [66].

Median filtering eliminates impulsive artifacts in an area smaller than half of the region being examined. When a speckle's size is larger than the filter's size, it remains unaltered [67]. Several adaptive filters have been studied [68-75]. They work well when applied to uncompressed backscattered envelope signals, but they are severely inaccurate with log-compressed signals. Moreover, the parameters (such as the size of the neighborhood, the structure, and the speckle thresholds) used in these methods may not correlate well with the actual speckle models [66]. Adaptive median filters have also been studied [76, 77]. Using these techniques, the pixel value is replaced by the weighted median of a local neighborhood whose size is determined according to the signal to noise ratio (SNR). Such techniques eliminate speckle artifacts smaller than half of the size of the region being examined; however, it also removes many important fine details [65].

A directional median filter is presented for boundary-preserving speckle reduction in [78]. The technique applies a bank of one-dimensional median filters, and retains the largest value among all filters' outputs at each pixel. The nonlinear diffusion method [64-80] can be regarded as an adaptive filter, whose diffusion (smoothing) direction and strength are controlled by an edge detection function. One speckle-reducing anisotropic diffusion (SRAD) [79] exploits an instantaneous coefficient of the variation as an edge detector for speckled imagery. However, the SRAD is only for uncompressed echo envelope images, and its performance declines when it is directly applied to logcompressed images. In addition, a speckle detector that simply combines the gradient magnitude and Laplacian may not perform well for the boundaries between regions with different gray levels. An approach for speckle reduction and coherence enhancement was presented based on a nonlinear coherent diffusion (NCD) model [66]. This approach combines three different models: isotropic diffusion, anisotropic coherent diffusion, and mean curvature motion. It changes progressively from isotropic diffusion through anisotropic coherent diffusion to, finally, mean curvature motion, thus producing speckle regions fully formed by maximally low-pass filtering, and substantially preserving information associated with the resolved-object structures. The disadvantage of the NCD model is that a nonselective Gaussian smoothing filter is needed before estimating structure tensors, which may eliminate feature details smaller than the smoothing kernel. A diffusion stick method for speckle suppression was presented in [80]. An asymmetric stick filter kernel is defined by decomposing the rectangle neighborhood into line segments of various orientations. However, it is sensitive to the size and shape of the stick. Moreover, the nonlinear diffusion technique relies on the gradient operator which cannot separate signal and noise precisely.

In summary, although some despeckle filters are said to be "edge preserving" and "feature preserving," they have limitations. In addition, despeckle filters are not directional [81].

#### 2.1.2 Wavelet-based Methods

In wavelet-based techniques, an image is decomposed into multiple scales, and various methods are used to reduce the speckle noise in multi-resolution domains. These are generally referred as wavelet shrinkage techniques. Wavelet shrinkage has been applied to speckle reduction of SAR images [82]. A soft thresholding method for denoising 1D signals was studied in [83].

Wavelet based techniques can be classified into two categories: thresholding and Bayesian framework. Most thresholding techniques [84-86] are based on softthresholding denoising, also referred to as wavelet shrinkage techniques. The signal is decomposed in the wavelet domain, and the obtained wavelet coefficients are softthresholded. The wavelet coefficients whose absolute values are below a threshold are replaced by zero, while the others are modified by shrinking toward zero.

Thresholding methods suffer from two major drawbacks. First, the problem of how to find the optimal solution for all types of images has not yet been solved. Second, it is unadvisable to use the same noise model for diverse resolutions, since the selected threshold may not match up well with the specific distribution of signal and noise components in all scales.

Nonlinear estimators based on Bayesian theory were developed in [87], and these outperform the classical linear processors and simple thresholding estimators. The authors used a generalized Laplacian model for the subband statistics of the signal and developed a noise-removal algorithm that performs a "coring" operation to preserve highamplitude observations while suppressing low-amplitude values from the high-pass bands. Wavelet-based denoising methods have also been developed within a Bayesian framework [88-91]. The logarithmic transform of the image is analyzed in the multiscale wavelet domain. Then, a Bayesian estimator is designed to exploit the sub-band decomposition statistics. Finally, an alpha-stable model is utilized to perform a nonlinear operation.

Most wavelet-based methods use a multiplicative model and take advantage of the logarithmical transformation to convert multiplicative speckle noise into additive noise. The common assumption in a large number of such studies is that the samples of the additive noise are mutually uncorrelated and obey a Gaussian distribution. However, as demonstrated both conceptually and experimentally in [65], this assumption is generally oversimplified and unnatural. Moreover, it may lead to an inadequate performance in speckle reduction. Table 2.1 summarizes speckle reduction methods [34].

Method	Description	Advantage	Disadvantage
Filtering Techniques	Use moving window to convolve the filter with the image to reduce speckle.	Simple and fast.	<ol> <li>Single scale representation is difficult to discriminate signal from noise.</li> <li>Sensitive to the size and shape of the filter window.</li> </ol>
Wavelet Domain	Transform image to wavelet domain and remove noise based on wavelet coefficients.	<ol> <li>When decomposed to wave- let domain, the statistics of many signals are simplified.</li> <li>Noise and signal are pro- cessed at different scales and orientations proportionally.</li> </ol>	Wavelet transformation and inverse wavelet transformation increase time complexity.

Table 2.1. Speckle Reduction Methods [34].

#### 2.2 Speckled Ultrasound Image Model

In order to reduce speckle noise in US images effectively, having precisely formulated models of speckled noise would be useful. However, a universally accepted speckle noise model is still under investigation. Nevertheless, a number of possible formulations are proposed. A generalized model of the speckle imaging [84, 88] is given by:

$$g(i, j) = f(i, j)u(i, j) + \xi(i, j)$$
(2.1)

where *g*, *f*, *u*, and  $\xi$  are the observed envelope image, original image, multiplicative, and additive components of the speckle noise, respectively.

Despite its possible theoretical shortcomings [92], the model in Eq.(2.1) has been used in ultrasound and SAR imaging. Moreover, when applied to US images, only the multiplicative component u of the noise need be reckoned with. Thus, the model in Eq. (1) can be simplified as:

$$g(i, j) \approx f(i, j)u(i, j) \tag{2.2}$$

There exists an alternative model [76, 86, 93], describing speckle noise as the additive noise, and its amplitude is proportional to the square root of the image. However, this model was proposed to account for a speckle pattern, as it appears "on screen," after a sequence of standard processing steps performed by a typical ultrasound scanner (e.g., nonlinear amplification, dynamic-range adjustment via logarithmic compression, etc.). Consequently, Eq. (2.2) assumes that the image g(i, j) has been observed before the process is applied.

To transform the multiplicative noise model into an additive one, the logarithmic function is applied to both sides of Eq. (2.2)

$$g_{i}(i,j) = f_{i}(i,j) + u_{i}(i,j)$$
(2.3)

where  $g_1$ ,  $f_1$  and  $u_1$ , are the logarithms of  $g_1$  and u, respectively.

After the image is applied by the logarithmic function, the speckle noise becomes an additive noise. Next, the speckle reduction process becomes one of rejecting an additive noise, and a variety of noise suppression techniques could be invoked to perform this task.

In this dissertation, the original US images are processed using the logarithm transformation, and the speckle noise is modeled as the additive noise.

#### 2.3 Proposed Method

In order to overcome the disadvantages of filters, we propose an algorithm for speckle reduction based on the textural homogeneity histogram. Homogeneity is used to describe the speckle characteristics. The homogeneity value is defined using the texture information and the image is transformed from the gray domain into the homogeneity domain. If the homogeneity value is high, the region is homogenous, and there are few speckles. Otherwise, the region is nonhomogenous, and speckles exist. A 2D homogeneity histogram is built, and the threshold is determined using the maximal entropy principle. The pixels are divided into two sets according to the threshold: a homogenous set Hs, and a nonhomogenous set, NHs. Finally, the pixels in the nonhomogenous set are handled according the neighbor pixels iteratively, and the speckle noise is removed without blurring the edges.

The proposed method includes four steps:

*Step 1*: Build a 2D homogeneity histogram using texture information;*Step 2*: Select threshold values based on the 2D homogeneity histogram in Step 1;

Step 3: Handle the nonhomogenous set using directional average filters;Step 4: Repeat Steps 1 through 3 until the termination criteria is satisfied.

#### 2.3.1 Building a 2D Homogeneity Histogram

#### 2.3.1.1 Texture Information Extraction

On ultrasound images of the human body, different organs and tissues have different texture information. Historically, texture has been utilized as an important feature for diagnosis, because texture analysis provides a good tool for detecting lesions and diagnosing diseases. In this chapter, Laws' texture energy measures (TEM) [37] are utilized to characterize the textural properties of an ultrasound image. TEM seeks to classify each pixel of an image by transforming each pixel into a texture energy plane. The transform is fast, requiring only convolutions and simple moving window techniques [94].

In the TEM method, texture in an image is described using five features: average gray level, edges, spots, ripples, and waves. These are derived from five simple onedimensional filters:

$$L5 = \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$
  

$$E5 = \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \end{bmatrix}$$
  

$$S5 = \begin{bmatrix} -1 & 0 & 2 & 0 & -1 \end{bmatrix}$$
  

$$W5 = \begin{bmatrix} -1 & 2 & 0 & -2 & 1 \end{bmatrix}$$
  

$$R5 = \begin{bmatrix} 1 & -4 & 6 & -4 & 1 \end{bmatrix}$$
  
(2.4)

where the masks *L5*, *E5*, *S5*, *W5* and *R5* are employed to detect level, edges, spots, ripples and waves features, respectively.

By mutually multiplying these five vectors, the four 5x5 Laws' masks:  $L5^T \times E5$ ,  $L5^T \times S5$ ,  $E5^T \times L5$  and  $S5^T \times L5$  are obtained [95]:
$$L5^{T} \times E5 = \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \\ -4 & -8 & 0 & 8 & 4 \\ -6 & -12 & 0 & 12 & 6 \\ -4 & -8 & 0 & 8 & 4 \\ -1 & -2 & 0 & 2 & 1 \end{bmatrix}$$

$$L5^{T} \times S5 = \begin{bmatrix} -1 & 0 & 2 & 0 & -1 \\ -4 & 0 & 8 & 0 & -4 \\ -6 & 0 & 12 & 0 & -6 \\ -4 & 0 & 8 & 0 & -4 \\ -1 & 0 & 2 & 0 & -1 \end{bmatrix}$$

$$E5^{T} \times L5 = \begin{bmatrix} -1 & -4 & -6 & -4 & -1 \\ -2 & -8 & -12 & -8 & -2 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 8 & 12 & 8 & 2 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

$$S5^{T} \times L5 = \begin{bmatrix} -1 & -4 & -6 & -4 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 8 & 12 & 8 & 2 \\ 0 & 0 & 0 & 0 & 0 \\ -1 & -4 & -6 & -4 & -1 \end{bmatrix}$$

The texture value of pixel (i, j), f(i, j), is computed:

$$f(i,j) = \sqrt{\left(f_{L5^{T} \times E5}(i,j)\right)^{2} + \left(f_{L5^{T} \times S5}(i,j)\right)^{2} + \left(f_{E5^{T} \times L5}(i,j)\right)^{2} + \left(f_{S5^{T} \times L5}(i,j)\right)^{2}}$$
(2.5)

where  $f_{L5^{T}\times E5}(i, j)$ ,  $f_{L5^{T}\times S5}(i, j)$ ,  $f_{E5^{T}\times L5}(i, j)$  and  $f_{S5^{T}\times L5}(i, j)$  are the convoluted results of the intensity g(i, j) with the four masks  $(0 \le i \le H - 1, 0 \le j \le W - 1)$ . *H* and *W* are the height and width of the image, respectively.

Next, the value of the texture information is normalized.

$$F(i, j) = \frac{f(i, j) - f_{min}}{f_{max} - f_{min}}$$
(2.6)

where  $f_{max} = max\{f(i, j)\}$  and  $f_{min} = min\{f(i, j)\} (0 \le i \le H - 1, 0 \le j \le W - 1)$ .

# 2.3.2.2 2D Homogeneity Histogram

The value of the homogeneity of each pixel is normalized into the range of [0, K](K is a constant to normalize the homogeneity values). Here, K = 100

$$Ho(i, j) = \lfloor K \times (1 - F(i, j)) \rfloor$$

$$(2.7)$$

The local mean value of homogeneity,  $\overline{Ho}(i, j)$ , is computed as:

$$\overline{Ho}(i,j) = \left[\frac{1}{w \times w} \sum_{m=i-(w-1)/2}^{i+(w-1)/2} \sum_{n=j-(w-1)/2}^{j+(w-1)/2} Ho(m,n)\right]$$
(2.8)

where w is the local widow size. Here, w = 5.

Finally, a 2D homogeneity histogram (homogram)  $h_{Ho,Ho}(m,n)$  is built based on Ho(i, j) and Ho(i, j).

$$h_{Ho,Ho}(m,n) = \sum_{0 \le i \le H-1, 0 \le j \le W-1}^{\frac{Ho}{Ho}_{min} \le m \le \frac{Mo}{Ho}_{max}} \delta\left(Ho(i,j) - m, \overline{Ho}(i,j) - n\right)$$
(2.9)

$$\delta(p,q) = \begin{cases} 1 & p = q = 0\\ 0 & otherwise \end{cases}$$
(2.10)

where  $Ho_{min}$  and  $Ho_{max}$  are the minimal and maximal homogeneity values,  $\overline{Ho}_{min}$  and  $\overline{Ho}_{max}$  are the minimal and maximal mean values of the homogeneity, respectively.

# 2.3.2 Select Threshold Values Based on 2D Homogeneity Histogram

First, the homogeneity of each pixel and the mean of the homogeneities of its neighborhood are calculated, and a 2D homogram is built. Next, the value of homogeneity threshold  $T(Ho_{th}, \overline{Ho}_{th})$  is determined based on the maximal entropy principle which is calculated from the 2D homogram. The pixels having the homogeneity values and mean values higher than  $T(Ho_{th}, \overline{Ho}_{th})$  are unchanged, and the other pixels are processed by the novel directional average filter. The process iterates until it stops.

An automatic method to determinate the homogeneity threshold is proposed based on the characteristics of the 2D homogram. Let Hop(i, j) be the probability distribution at the homogeneity *i* and mean homogeneity *j*, *i*, *j* = 1,2,....,*N*.

 $N = \left[ max(Ho(m,n), Ho(m,n)) \right]$ . Two groups, HoF and HoB, are classified according to

the threshold, representing the foreground and background in the homogeneity domain, and their entropies are defined as:

$$H_{HoB}(s,t) = -\sum_{i=1}^{s} \sum_{j=1}^{t} \frac{Hop(i,j)}{HoP(s,t)} \ln \frac{Hop(i,j)}{HoP(s,t)}$$
(2.11)

$$H_{HoF}(s,t) = -\sum_{i=s+1}^{N} \sum_{j=t+1}^{N} \frac{Hop(i,j)}{1 - HoP(s,t)} \ln \frac{Hop(i,j)}{1 - HoP(s,t)}$$
(2.12)

$$Hop(i,j) = \frac{1}{H \times W} h_{ho,\overline{ho}}(i,j)$$
(2.13)

$$HoP(s,t) = \sum_{i=1}^{s} \sum_{j=1}^{t} Hop(i,j)$$
(2.14)

where  $H_{HoF}(s,t)$  represents the 2D entropy of the foreground and  $H_{HoB}(s,t)$  represents the 2D entropy of the background. HoP(s,t) is the sum of HoP(i, j) whose coordinates are lower than (s,t).

The maximum entropies of the foreground and background are computed, and the threshold can be obtained by:

$$T(HO_{th}, \overline{HO}_{th}) = \operatorname{Arg\,max}_{1 \le s \le N} \left\{ H_{HoF}(s, t) + H_{HoB}(s, t) \right\}$$
(2.15)

Once the threshold  $T(Ho_{th}, Ho_{th})$  is obtained, the pixels are divided into two sets,

Hs and NHs:

$$Hs = \{P(i, j), Ho(i, j) \ge Ho_{ih} \text{ and } Ho(i, j) \ge Ho_{ih}\}$$
(2.16)

$$NHs = \{P(i, j), Ho(i, j) \le Ho_{th} \text{ or } Ho(i, j) \le Ho_{th}\}$$
(2.17)

where Hs is the homogenous set and NHs is the nonhomogenous set. P(i, j) is the pixel at the coordinates (i, j).

#### 2.3.3 Handling the Nonhomogenous Set

The nonhomogenous pixels are handled by the novel directional average filters (DAF) to reduce the speckle noise, and the pixels on the edges become more distinct:

$$\tilde{g}(i,j) = \begin{cases} g(i,j) & (i,j) \in Hs \\ DAF(g(i,j)) & (i,j) \in NHs \end{cases}$$
(2.18)

where  $DAF(\bullet)$  is the directional average filter function.

The conventional average filter has no directions, and it removes noise while making the edge blurry. However, the proposed directional average filter can reduce noise and enhance the edge at the same time.

A pixel direction is determined according to neighboring information. In Figure 2.1(a), the pixel direction is called all-directional. The pixel direction is horizontal in Figure 2.1(b), and the pixel direction is vertical in Figure 2.1(c). If the value of the horizontal edge is higher than the value of the vertical edge, the pixel direction is horizontal; if the value of the vertical edge is higher than the value of the horizontal edge, the pixel direction is vertical; otherwise, the pixel direction is all-directional.



Figure 2.1. A pixel's direction.

A Sobel operator [96], whose function is \an edge operator, is utilized to compute the edge values because of its high speed and simplicity. The edge values are normalized:

$$Eh(i, j) = \frac{e_{h}(i, j) - e_{min}}{e_{max} - e_{min}}$$
(2.19)

$$Ev(i, j) = \frac{e_v(i, j) - e_{min}}{e_{max} - e_{min}}$$
(2.20)

where  $e_h(i, j)$  and  $e_v(i, j)$  are the absolute values of the horizontal and vertical edge values obtained using the Sobel operator,  $e_{max} = max(e_h(i, j), e_v(i, j))$ , and

$$e_{\min} = min(e_{\mu}(i, j), e_{\nu}(i, j)) \ (0 \le i \le H - 1, \ 0 \le j \le W - 1).$$

The image is processed by a directional average filter (DAF). The DAF has three masks according to the pixels' directions:

$$M_{1} = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad M_{2} = \frac{1}{3} \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad M_{3} = \frac{1}{3} \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$
(2.21)

$$R_{1} = \operatorname{cov}(M_{1}, I) \quad R_{2} = \operatorname{cov}(M_{2}, I) \quad R_{3} = \operatorname{cov}(M_{3}, I)$$
(2.22)

where  $M_1$ ,  $M_2$ , and  $M_3$  are the masks with a 3x3 size to process all-directional,

horizontal, and vertical pixels, respectively.  $R_1$ ,  $R_2$ , and  $R_3$  are the filtering results when the image is convoluted with  $M_1$ ,  $M_2$  and  $M_3$ , and  $cov(\bullet)$  is the convolution function.

The function of the directional average filter *DAF* is defined as:

$$DAF(g(i, j)) = \begin{cases} R_1 & Eh(i, j) = Ev(i, j) \\ R_2(1 + \delta_i) & Eh(i, j) > Ev(i, j) \\ R_3(1 + \delta_i) & Eh(i, j) < Ev(i, j) \end{cases}$$
(2.23)

where  $\delta_i$  is the variance in the local window. If Eh(i, j) = Ev(i, j), the region is smooth, and the result after average filtering replaces the current intensity; and if  $Eh(i, j) \neq Ev(i, j)$ , the edges exist in the local region, and the edge values are enhanced and replaced by the weighted directional filtering results.

### 2.3.4 Terminating the Iterative Process

After the pixels in the nonhomogenous set are handled by the iterative process, the speckle noise decreases. If the iterative process is conducted, most of the speckle noise can be eliminated, while the edges and details are preserved. A criterion should be used to terminate the iterative process. We use the homogenous ratio HR as the criterion to terminate the iterative process. If HR is low, the image is nonhomogeneous, and the iterative process should continue. Otherwise, the iterative process should stop.

The homogenous ratio is defined as:

$$HR = \frac{Num(Hs)}{H \times W}$$
(2.24)

where Num(Hs) is the number of elements in Hs. H and W are the height and width of the image, respectively.

The procedure to terminate the iterative process is as follows:

Step 1: Calculate *HR*[*i*];

Step 2: If HR[i] > HRTh, then terminate the process;

Else i = i + 1 go to Step 1;

The value of HRTh is determined experimentally, and for our purposes is equal to 0.9.

The directional average filters are employed iteratively to remove noise, make the image more homogenous, and increase the homogenous ratio. Finally, it reaches convergence and terminate the process.

# 2.4 Experimental Results and Discussion

Various breast ultrasound images were used in the experiments. To assess the performance of the proposed method, the results by the proposed method were compared with those obtained by a wavelet based method [85] and median filter.

### 2.4.1 Performance Evaluation on Synthetic Images

There is no speckle–free US image in reality, and there is not a universally accepted criterion for evaluating the performance of the speckle reduction algorithms as well. We start with a synthetic image first. Figure 2.2(a) is a synthetic image with two intensities: 63 and 127. Figure 2.2(b) is an image with speckle noise. Figure 2.2(c) is the result obtained by the wavelet based method [85]. Figure 2.2(d) and (e) are the results obtained after applying the median filter and Wiener filter, respectively. Figure 2.2(f) is the result obtained after applying the proposed approach.

In order to quantify the performance of the methods, some metrics were studied. Although the signal to noise ratio (SNR) was used to assess noise reduction for many applications, it is not adequate to evaluate suppression performance of multiplicative noise. To solve this problem, the signal-to-mean square error (SMSE) ratio is employed [88]. In our experiments, three metrics: SMSE, coefficient of correlation  $\rho$  and edge preservation measure  $\beta$  [97], were computed for the "noise-free" and processed images, respectively.



Figure 2.2. A synthetic image. (a) The synthetic noise-free image. (b) image (a) speckle noise added. (c) result of the median filter. (d) result of the Wiener filter. (e) result of the wavelet based approach. (f) result of the proposed method.

The signal-to-MSE (SMSE) ratio was calculated to evaluate the noise suppression for the multiplicative noise:

$$SMSE = 10 \log_{10} \left( \frac{\sum_{i=1}^{K} S_i^2}{\sum_{i=1}^{K} (\hat{S}_i - S_i)^2} \right)$$
(2.25)

where  $S_i$  is the *ith* pixel in the original image,  $S_i$  is the *ith* pixel in the image after speckle reduction, and  $\kappa$  is the image size.

We are interested in not only suppressing speckle noise, but also in preserving the edges which often constitute features for diagnosis. Hence, we also utilize the correlation measure  $\rho$  and edge preservation measure  $\beta$  [97]:

$$\rho = \frac{\Gamma(S - \overline{S}, S - \overline{S})}{\sqrt{\Gamma(S - \overline{S}, S - \overline{S}) \cdot \Gamma(S - \overline{S}, \Delta S - \overline{S})}}$$
(2.26)

$$\beta = \frac{\Gamma(\Delta S - \overline{\Delta S}, \Delta S - \overline{\Delta S})}{\sqrt{\Gamma(\Delta S - \overline{\Delta S}, \Delta S - \overline{\Delta S}) \cdot \Gamma(\Delta S - \overline{\Delta S}, \Delta S - \overline{\Delta S})}}$$
(2.27)

$$\Gamma(S_i, S_i) = \sum_{i=1}^{K} S_i \cdot S_i$$
(2.28)

where *s* and *s* are the original image and the image after speckle reduction, and  $\overline{s}$  and  $\overline{s}$  are the mean values of *s* and *s*, respectively.  $\Delta s$  and  $\Delta s$  are the high-pass filtered versions of *s* and *s* obtained with a 3×3 Laplacian operator, and  $\overline{\Delta s}$  and  $\overline{\Delta s}$  are the mean values of  $\Delta s$  and  $\Delta s$ , respectively.

To evaluate the performance quantitatively, the US images with different levels of speckle noise can be produced [88]:

$$I(i, j) = S(i, j) \times V(i, j)$$
(2.29)

where S(i, j) is the reference, noise-free ultrasound image and V(i, j) is a unit mean complex Gaussian random field. By changing the variance of the Gaussian random field, images with different noise levels can be generated.

The comparisons of SMSE,  $\rho$  and  $\beta$  between the wavelet-based method, median filter, Wiener filter, and the proposed method are shown in Figures 2.3, 2.4 and 2.5, respectively. We can see that the values of SMSE,  $\rho$  and  $\beta$  of the proposed method are higher than those of the wavelet-based approach, median filter, and Wiener filter at all noise levels, thus demonstrating that the proposed method performs better than the wavelet-based approach, median filter, and Wiener filter both in suppressing speckle noise and preserving the edges.



Figure 2.3. Comparison of SMSE using different speckle reduction methods: \*: the proposed method; x: the wavelet based method; o: the Wiener filter; +: median filter.



Figure 2.4. The curve of Rho using different speckle reduction methods: \*: the proposed method; x: the wavelet based method; o: the Wiener filter; +: median filter.



Figure 2.5. The curve of Beta using different speckle reduction methods: \*: the proposed method; x: the wavelet based method; o: the Wiener filter; +: median filter.

### 2.4.2 Experiments on Breast Ultrasound Images

We assessed the performance of the proposed method using clinical BUS images. As mentioned before, there is no clinical speckle-free ultrasound image. Therefore, we used images processed by a homomorphic Wiener filter to approximate speckle-free images [85]. In order to compare the proposed method and the wavelet-based method, we adopted the approach to obtain the speckle-free images [85].

Figures 2.6(a), 2.7(a), 2.8(a), and 2.9(a) are the original images, Figures 2.6(b)through 2.9(b) are the results obtained by using the wavelet-based method [85], and Figures 2.6(c) through 2.9(c) are the results obtained by using the proposed algorithm. The values of the three metrics are described in Table 2.2. From the metrics values in Table 2.2 clearly indicates that the proposed method performs better than the waveletbased approach not only in speckle noise reduction but also in edge preservation.

Figure 2.6(a) has a loose mass at the right region, which is an important feature in distinguishing malignant tumors. The mass is affected by speckle noise, and the edges are unclear. The situation is not improved much in Figure 2.6(b). However, in Figure 2.6(c), the speckles on the mass are removed, and the edges become distinct. In addition, some of the speckles appear in the middle line-like area, which relate to the muscle's texture characteristics. In Figure 2.6(b), the speckles are not depressed enough; however, they are reduced effectively in Figure 2.6(c). Severe speckle noise appears in Figure 2.7, and many regions have become nonhomogenous. In Figure 2.7(c), the lesion features are significantly improved. Figures 2.8 and 2.9 also compare performance on speckle reduction and edge preservation, and clearly demonstrate that the proposed approach outperforms other methods.

Image	Wavelet-based method			The proposed method			
	SMSE	ρ	β	SMSE	ρ	β	
Figure 2.6	17.81	0.54	0.53	22.98	0.95	0.93	
Figure 2.7	17.62	0.62	0.61	18.05	0.79	0.72	
Figure 2.8	17.75	0.63	0.61	21.58	0.73	0.66	
Figure 2.9	16.17	0.50	0.49	18.02	0.81	0.75	

Table 2.2. Metric Comparison Between Two Methods.



(a)



Figure 2.6. First example of breast ultrasound image and its results after speckle reduction. (a) Clinical BUS image. (b) Result using the wavelet-based approach. (c) Result using the proposed method.



(c) Figure 2.7. Second example of breast ultrasound image and its results after speckle reduction. (a) Clinical BUS image. (b) Result using the waveletbased approach. (c) Result using the proposed method.



Figure 2.8. Third example of breast ultrasound image and its results after speckle reduction. (a) Clinical BUS image. (b) Result using the waveletbased approach. (c) Result using the proposed method.



Figure 2.9 Fourth sample of breast ultrasound image and its results after speckle reduction. (a) Clinical BUS image. (b) Result using the wavelet based approach. (c) Result using the proposed method.

#### 2.4.3 Experiments on Vascular Ultrasound Images

In order to test performance on edge perseveration, we evaluated the proposed method using some clinical vascular images. Figures 2.10(a) and 2.11(a) are the original images, and Figures 2.10(b) and 2.11(b) are the results by the proposed algorithm.

Figure 2.10 is a cross section of the carotid, in which the circular boundary of the carotid is blurry and corrupted by speckle noise. In Figure 2.10(b), the circular boundary of the carotid becomes distinct, and the noise is removed.

Furthermore, in Figure 2.11, some horizontal edges become broken due to speckle noise, whil in Figure 2.11(b), these edges are significantly enhanced. Figures 2.10 and 2.11 demonstrate that the proposed approach performs better in speckle reduction and edge preservation.

# 2.4.4 Experiments on Clinical Breast Cancer Diagnosis

To evaluate its performance, we applied the proposed method to clinical breast ultrasound (BUS) images. The breast ultrasound images used in the experiments were provided by the Second Affiliated Hospital of Harbin Medical University, Harbin, China. The images were collected by using a VIVID 7 (GE, USA) with a 5-14 MHz linear probe, and captured directly from video signals.

The database consists of 349 images of 115 cases, and each single lesion is in one image. Of the 115 cases, 59 were benign solid lesions (165 images), and 56 were malignant solid lesions (184 images). All lesions were confirmed by biopsy or operation, and the tumors were outlined by radiologists. 349 original images were processed using the proposed algorithm. The original images and speckle-reduced images were randomly given to experienced radiologists who did not know the initial diagnostic results.



Figure 2.10. First example of vascular ultrasound image and the result after speckle reduction. (a) Original vascular ultrasound image. (b) Result using the proposed method.



Figure 2.11. Second example of vascular ultrasound image and the result after speckle reduction. (a) Original vascular ultrasound image. (b) Result by the proposed method.

The diagnosis results were divided into five categories: (1) benign, (2) probably benign, (3) possibly benign/malignant, (4) probably malignant, and (5) malignant. The results before and after speckle reduction were tested by Chi-square method in a  $2\times 2$  table. The diagnostic results by radiologists based on the original images and speckle-reduced images are shown in Tables 2.3 and 2.4, respectively.

Using the proposed method, after the speckles in the BUS images are removed and the edges are preserved, the images become distinct, the regions become more homogeneous, and the boundaries of the regions are distinct, making them more suitable for mass detection and classification.

The diagnosis results in Tables 2.3 and 2.4 show that a definitive and correct diagnosis can be increased from 61 cases of the original images (32 malignant cases and

Table 2.3. Ultrasound Diagnostic Results Based on the Original Images.

Ultrasound	benign	probably	possibly	probably	malignant	Total
Pathology	beingn	benign	benign/malignant	malignant		
benign	29	9	11	5	5	59
malignant	4	3	7	10	32	56

Table 2.4. Ultrasound Diagnostic Results Based on the Speckle Reduction Images.

Ultrasound	benign	probably	possibly	probably	malignant	Total
Pathology		benign	benign/malignant	malignant		
benign	38	8	8	4	1	59
malignant	1	2	4	6	43	56

29 benign cases) to 81 cases of the speckle-reduced images (43 malignant cases and 38 benign cases).

The breast cancer diagnosis results were evaluated using a receiver operating characteristic (ROC) curve based on the above sensitivity and specificity values, as shown in Figure 2.12. The diagnostic sensitivity and specificity were calculated by the areas (Az) under the ROC curves. The results indicate that the value of Az without speckle reduction was 0.843 compared to 0.955 with speckle reduction using the proposed approach. An analysis of the original images yielded an area Az1 (0.843) under the ROC curve, and its 95% confidence interval was [0.769, 0.917]. While the analysis of the speckle-reduced images yielded an area Az2 value (0.955) under the ROC curve, and its 95% confidence interval was [0.917, 0.992]. Thus, using the speckle reduction algorithm greatly improves the accuracy of diagnosis of the breast lesions.



Figure 2.12. ROC curves using the original and speckle reduced BUS images.

The experiments have shown that the proposed approach can significantly enhance the contours and the fine details of US images. While enhanced images can be processed further to detect the tumors with an even higher accuracy, the proposed speckle reduction method is very useful for CAD systems using ultrasound medical images.

### **2.5 Conclusions**

In this chapter, a novel speckle-suppression algorithm using a 2D homogram and directional average filter is developed. The local homogeneity defined by the texture information is used to describe speckle noise, and the pixels are divided into a homogenous set and a nonhomogenous set based on the homogeneity threshold value obtained using the maximum 2D entropy principle. The pixels in the nonhomogeneous set are handled by the directional average filters iteratively.

All the parameters for describing speckle noise and terminating the iterative process are derived automatically based on the characteristics of the given US images. The experimental results demonstrate that the proposed approach can remove speckle noise and preserve the edges and details of the US images at the same time. The proposed algorithm has a better performance than that of the existing algorithms, it is likely this approach will find wide application in ultrasound imaging.

#### CHAPTER 3

### ENHANCEMENT OF BREAST ULTRASOUND IMAGES

Breast cancer is a serious disease that can prove fatal if not caught early. Thus, early detection is essential. Breast ultrasound images have been proven to be a valuable adjunct to mammography in the detection and classification of breast lesions. Due to their fuzzy and noisy nature and the low contrast of ultrasound images, however, it is difficult to provide accurate and effective diagnose using ultrasound images. Image enhancement is used to improve the quality of the image and to correct deficiencies of the contrast. Breast ultrasound images have low contrast and some degree of fuzziness such as indistinct cyst borders, ill-defined mass shapes, and different tumor densities.

# 3.1 Summary of Breast Ultrasound Image Enhancement Methods

### 3.1.1 Filtering Methods

Some nonlinear filters have been used to enhance the ultrasound images. For example, [98] presents a morphological method, alternating sequential filter (ASF), that enhance ultrasound images. It is difficult to enhance the image and suppress noise at the same time. One group of researchers [99] adopts a nonlinear enhancing filter based on sorting the elements in a moving window and extracting statistical characteristics from them. The filter compares the statistical values of the front and back points to those of the point centered in the window. It next estimates the output using the compared result. However, the enhancement is affected by the size of filters. How to determine the size and number of filters is not discussed in detailed.

Many nonlinear or linear map functions are used to enhance the contrast of

ultrasound image in the space domain or other domains. The authors of [100] apply the gray level mapping technique (GLM) to further enhance ultrasound images of different contrast levels and brightness. GLM is a technique that maps the input gray level (low and high) to the stretched output gray level (bottom and top) observed in a look-up table. The mapping function is an exponential function, and its parameter is a constant that does not change with different images. A nonlinear algorithm [101] has been studied for contrast enhancement accomplished via nonlinear stretching followed by hard thresholding of wavelet coefficients within midrange spatial frequency levels. The selection of the threshold is subjective, and the enhancement depends a great deal on the selection of hard threshold.

An algorithm [102-105] called sticks is used to enhance the contrast of ultrasound images. In it, line segments (called "sticks") in different angular orientations are used as templates for selecting the orientation at each point that is most likely to represent a line in an image to improve edge information. Thus, sticks are more suitable for edge detection than some other methods. However, the algorithm only enhances edge information, and the features inside the lesions are not paid enough attention.

The authors of [106] use Laplacian pyramid-based nonlinear diffusion and shock filter (LPNDSF) for ultrasound image enhancement. In this method, a coupled nonlinear diffusion and shock filter process is applied in a Laplacian pyramid domain of an image to enhance edges.

The authors of [33] present an adaptive image enhancement method through selected dynamic filtering for ultrasound images. It enhances the tissue structure and also smoothes the speckle regions adaptively from predefined filters. The criterion of a speckle region is defined from a similarity value obtained from histogram matching between the histogram in the processing window and a reference derived from a speckle area. Large similarity values mean the speckle pixels need smoothing from low pass filtering, and small values correspond to structure pixels that are enhanced by high pass filters. All these filters can be implemented as dynamic filtering whose index is the similarity value for adoptively smoothing speckle for contrast enhancement or enhancing structure for better edge/boundary detection.

An adaptive pyramid filtering method is presented in [107] that increases an ultrasound image's contrast. The image is first decomposed into multi-resolution representations using the Laplacian pyramid (LP). Each LP layer is then filtered with an adaptive filter to smooth noise and save features at the same time. The controlling parameter of the filter at each LP layer is calculated using local statistics, and the transformation function of the equivalent filters related to the LP layer. The output image is then reconstructed from the filtered LP layers.

The approach proposed in [108] bases ultrasound image enhancement on a perceptual saliency measure. The boundaries of tissues in US images are enhanced by computing the saliency of directional vectors in the image space. The measure is generally determined by curvature changes, intensity gradient, and the interaction of neighboring vectors.

The authors of [109] modified the existing framework of an adaptive filtering mechanism to enhance and preserve important, typically anisotropic, image structures. This filtering technique facilitates user interaction and direct control over high frequency contents of the signal. Local structure analysis is performed based on tensor estimation with an optimized set of spherical harmonic filters.

The research presented in [110] investigates the use of morphology-based nonlinear filters, and performs deterministic and statistical analysis of the linear combinations of the filters for the image enhancement of B-mode ultrasound images. Initially, five different images were morphologically filtered using ten different structuring elements, and the filtered images were assessed quantitatively. A subjective analysis by radiologists indicates that a morphological filter using line shaped structuring element with length 2 performs better than other structuring elements.

A filtering technique has been applied to the wavelet domain for enhancement. The authors of [111] propose a nonhomomorphic filtering method, namely, GenLik, in the wavelet domain. The GenLik method employs a preliminary detection of the wavelet coefficients to empirically estimate the statistical distributions of signal and noise. Another team of researchers [112] propose an ultrasound image enhancement method based on the combination of the GenLik method and the local Wiener filtering technique in the wavelet packet transform domain. First, the method decomposes an ultrasound image into wavelet packet transform (WPT) subbands. For each detail subband, the method filters WPT coefficients using a local Wiener filter, and uses the joint to detect and an estimation function to compute the estimated value of each coefficient. Finally, the enhanced image is reconstructed using the processed detail subbands and the coarse subbands.

# 3.1.2 Histogram Equalization Method

The histogram equalization (HE) method has been improved upon for ultrasound image contrast enhancement. The authors of [113] employ a multi-peak generalized

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histogram equalization (GHE) method [114] to enhance a breast ultrasound image. Presented in [50] is an entropy-based local histogram equalization (LHE) algorithm to ultrasound image enhancement achieved by using the local entropy value of a subblock to decide whether LHE is applied on the center pixel of this subblock.

### 3.1.3 Fuzzy Set Methods

Fuzzy set theory [115, 116] has been employed to enhance ultrasound images. In fuzzy set methods, the image is first transformed into the fuzzy domain using the membership function. Next, the membership function is enhanced by an iterative 4segment function. However, the rules of the iterative 4-segment function and the number of iterations are fixed and determined subjectively. Also, the method just used global features, and cannot reflect the local contrast change.

There are some other methods for breast ultrasound image enhancement. A statistical model using tissue properties and intensity nonhomogeneities in ultrasound has been used for contrast enhancement and image segmentation. The maximum a posteriori (MAP) principle has been used to correct tissue intensity and to conduct contrast enhancement of breast ultrasound images [117]. The method modifies the distribution of the intensities, and does not pay much attention to the features of tumors and tissues.

### **3.2 Proposed Method**

We present a novel enhancement algorithm based on fuzzy logic and homogeneity with the ability to enhance the fine details of an ultrasound image, while avoiding noise amplification and over enhancement. The maximum fuzzy entropy principle is used to map the original image. The characteristics of ultrasound image are then taken into account. Specifically, edge and textural information is extracted to evaluate the lesions' features and the scattering phenomenon of ultrasound images. The local information is used to define the enhancement criterion. It enhances the image using both local and global fuzzy information. To demonstrate the performance of the proposed approach, the algorithm was tested on a large number of breast ultrasound images. Experimental results, presented in Section 3.3, confirm that the proposed method effectively enhances the details of the breast lesions without over-enhancement and under-enhancement.

Among the early indicators of breast cancers, masses and microcalcifications are the primary features and important visual indicators for early cancer detection [118, 119]. Unfortunately, in the early stages of breast cancer, the inside structure and border of masses of ultrasound images are very subtle and varied in appearance, making diagnosis very difficult. The difference between the suspicious areas and normal tissues can be very slight. Breast ultrasound image enhancement, especially for images of dense breasts, is very important for both the doctors and computer-aided diagnosis systems. Enhancement allows for more useful information to be extracted for diagnosis.

The proposed method consists of five steps: gray level normalization, image fuzzification, edge information extraction, textural information extraction, and contrast enhancement.

# 3.2.1 Gray-level Normalization

The distribution of gray levels of breast ultrasound images may vary greatly; however, the ranges of the intensities are narrow. Normalization is a necessary step, and we normalize the ultrasound image by mapping the intensity levels into the range  $[g_{\min}, g_{\max}]$ :

$$g(i, j) = g_{\min} + \frac{(g_{\max} - g_{\min}) \times (g_o(i, j) - g_{o\min})}{(g_{o\max} - g_{o\min})}$$
(3.1)

where  $g_{omin}$  and  $g_{omax}$  are the minimum and maximum intensity levels of the original image,  $g_{min}$  and  $g_{max}$  are the minimum and maximum intensity levels of the normalized image, and  $g_o(i, j)$  and g(i, j) are the gray levels at the coordinates (i, j) before and after normalization, respectively.

### 3.2.2 Image Fuzzification

In order to apply fuzzy logic to deal with the fuzziness of A breast ultrasound image, a suitable membership function is selected to map all the elements of a set into real numbers in the range [0, 1]. The values of the function represent the brightness degree of the pixel intensities. The most commonly used membership function for a gray level image is the standard S function [120] as shown in Figure 3.1:

$$S(g; x, y, z) = \begin{cases} 0 & g \le x \\ \frac{(g-x)^2}{(y-x)(z-x)} & x \le g \le y \\ 1 - \frac{(g-z)^2}{(z-y)(z-x)} & y \le g \le z \\ 1 & g \ge z \end{cases}$$
(3.2)

In the S function equation, the selection of the middle point y can be determined as an object-background classification problem [121] using the entropy principle [122, 123]. Let  $p_i$  be the probability distribution of the grey levels  $i, i = 1, 2, \dots, N$ . The distributions of intensity levels are as follows.



The intensity levels less than or equal to t are:

$$\frac{p_1}{P_t}, \frac{p_2}{P_t}, \dots, \frac{p_t}{P_t}$$
 (3.3)

and the intensity levels greater than t are:

$$\frac{P_{t+1}}{1-P_t}, \frac{P_{t+2}}{1-P_t}, \dots, \frac{P_N}{1-P_t}$$
(3.4)

$$P_{t} = \sum_{i=1}^{t} p_{i}$$
(3.5)

where t is the threshold, and N is the maximum intensity of the image.

The entropies of the distributions less than or equal to, and greater than the threshold t can be defined as  $H_1(t)$  and  $H_g(t)$ , respectively:

$$H_{I}(t) = -\sum_{i=1}^{t} \frac{P_{i}}{P_{t}} \ln \frac{P_{i}}{P_{t}}$$
(3.6)

$$H_{g}(t) = -\sum_{i=t+1}^{N} \frac{P_{i}}{1 - P_{t}} \ln \frac{P_{i}}{1 - P_{t}}$$
(3.7)

The maximum information of the entire distribution can be obtained by:

$$t^{*} = Arg \max_{t=1}^{N} \left\{ H_{l}(t) + H_{g}(t) \right\}$$
(3.8)

where  $t^*$  is the optimal threshold. The value  $t^*$  is used as the middle point of the S function. The ultrasound image is transformed from the intensity domain into fuzzy domain using the S function:

$$\mu(i, j) = S(g(i, j); x, t^*, z)$$
(3.9)

$$h_{g}(m) = \sum_{m=0}^{0 \le j \le W-1} \delta\left(g(i,j) - m\right)$$
(3.10)

$$\delta(t) = \begin{cases} 1 & t = 0 \\ 0 & otherwise \end{cases}$$
(3.11)

where g(i, j) is the intensity at the coordinates (i, j),  $h_g(m)$  is the gray level histogram, m is the gray level, and H and W are the height and width of the image. The values of x and z are the gray levels corresponding to the first peak and last peak of  $h_g(m)$ ,

respectively. If  $(h_g(n) > h_g(n-1)) \cap (h_g(n) > h_g(n+1))$ , then  $h_g(n)$  is a peak.

### 3.2.3 Edge Information Extraction

Among the early indicators of breast cancer, the mass's shape and margin, and the membrane's smoothness are primary features. In order to obtain the edge feature, an edge operator is applied to the fuzzified image:

$$e_{\mu}(i,j) = \frac{\delta_{\mu}(i,j) - \delta_{\mu\min}}{\delta_{\mu\max} - \delta_{\mu\min}}$$
(3.12)

where  $\delta_{\mu}(i, j)$  is the edge value by using the Sobel operator [124], and

$$\delta_{\mu \max} = \max(\delta_{\mu}(i, j)), \ \delta_{\mu \min} = \min(\delta_{\mu}(i, j)) \ \left(0 \le i \le H - 1, 0 \le j \le W - 1\right).$$

# 3.2.4 Texture Information Extraction

There are many methods used for describing texture features. One method [15] computed 28 descriptors at five different neighborhood sizes to make a total of 140 descriptors. Another algorithm [125] studied the classification of ultrasonic liver images by using texture features: the spatial gray-level difference statistics, the Fourier power spectrum, the gray-level difference statistics, and the Laws' texture energy measures [126].

Scattering phenomenon is the main characteristic of ultrasound images and occurs when tissues are rough or smaller than the scale of the wavelength. Many small lesion and tissue features can be gained from scattering on ultrasound images. In the proposed method, the Laws' texture energy measures (TEM) are used to determine the textural properties of ROIs in the fuzzy domain. Four masks,  $L5^T \times E5$ ,  $L5^T \times S5$ ,  $E5^T \times L5$ , and  $S5^T \times L5$ , are used to depict the edge and spot features of scattering.

The texture value of the pixel at coordinate (i, j),  $f_{\mu}(i, j)$  is used to describe the textural information as:

$$f_{\mu}(i,j) = \frac{abs(f_{\mu L5^{T} \times E5}(i,j))}{f_{\mu L5^{T} \times E5 \max}} \times \frac{abs(f_{\mu L5^{T} \times 55}(i,j))}{f_{\mu L5^{T} \times 55 \max}} \times \frac{abs(f_{\mu E5^{T} \times L5}(i,j))}{f_{\mu E5^{T} \times L5 \max}} \times \frac{abs(f_{\mu E5^{T} \times L5}(i,j))}{f_{\mu S5^{T} \times L5 \max}} (3.13)$$

where  $f_{\mu L S^{T} \times E S}^{(i, j)}$ ,  $f_{\mu L S^{T} \times S S}^{(i, j)}$ ,  $f_{\mu E S^{T} \times L S}^{(i, j)}$  and  $f_{\mu S S^{T} \times L S}^{(i, j)}$  are the convoluted results of the  $\mu(i, j)$  with the four masks, and  $f_{\mu L S^{T} \times E S \max} = \max(abs(f_{\mu L S^{T} \times E S}^{(i, j)}(i, j)))$ ,

$$f_{\mu L S^T \times S S \max} = \max(abs(f_{\mu L S^T \times S S}(i, j))), f_{\mu E S^T \times L S \max} = \max(abs(f_{\mu E S^T \times L S}(i, j)))$$
 and

$$f_{uss^{T}\times LSmax} = \max(abs(f_{uss^{T}\times LS}(i, j)))$$
, respectively  $(0 \le i \le Height - 1, 0 \le j \le Width - 1)$ .

# 3.2.5 Contrast Enhancement

In the proposed method, the image is enhanced by modifying the contrast ratio in the fuzzy domain. Several propsed methods use analytic functions [127, 128] or charts [129] to increase the contrast ratio.

The contrast ratio is defined in the fuzzy domain. Many definitions of contrast have been studied [130]. Usually, the contrast *C* is defined as [129]:

$$C = \frac{(f-b)}{(f+b)} \tag{3.14}$$

where f is the maximum intensity and b is the minimum intensity of the image.

The contrast ratio is defined in fuzzy domain as follows:

$$C_{\mu}(i,j) = \left| \mu(i,j) - \overline{\mu}_{w}(i,j) \right| / \left| \mu(i,j) + \overline{\mu}_{w}(i,j) \right|$$
(3.15)

$$\overline{\mu}_{w}(i,j) = \frac{\sum_{m=i-(w-1)/2}^{i+(w-1)/2} \sum_{m=j-(w-1)/2}^{j+(w-1)/2} (\mu(m,n) \times f_{\mu}(m,n) \times e_{\mu}(m,n))}{\sum_{m=i-(w-1)/2}^{i+(w-1)/2} \sum_{m=j-(w-1)/2}^{j+(w-1)/2} f_{\mu}(m,n) \times e_{\mu}(m,n)}$$
(3.16)

where  $\overline{\mu}_{w}(i, j)$  is the local mean of the window whose size is  $w \times w$  and centered at location (i, j).

The new contrast C' is obtained by using a nonlinear function of C or an empirically determined relationship between C' and C. Previously, analytic functions (square root, exponential, and logarithm) were used [127, 128]. However, it was found that an empirically formed chart or plot defining the relationship between C' and C gives better results [129]. Additioanlly, the authors of [131] use a class of modified

sigmoid functions to enhance the ultrasound image.

An exponential function k(i, j) transforms  $C_{\mu}$  into  $C'_{\mu}$ , which boosts the perceptibility of regions with low contrast while not affecting high-contrast regions. k(i, j) is determined according to the nature of the original image automatically. Consider:

$$C'_{\mu}(i,j) = \left(C_{\mu}(i,j)\right)^{k(i,j)}$$
(3.17)

where k(i, j) is the local contrast amplification constant of pixel (i, j). The exponential function significantly affects the degree of the contrast enhancement. How to determine the value of k(i, j) will be discussed later.

The modified membership value  $\mu'(i, j)$  of pixel (i, j) can be obtained by:

$$\mu'(i,j) = \begin{cases} \frac{\overline{\mu}_{w}(i,j)(1+C'_{\mu}(i,j))}{(1-C'_{\mu}(i,j))} & \mu(i,j) \ge \overline{\mu}_{w}(i,j) \\ \frac{\overline{\mu}_{w}(i,j)(1-C'_{\mu}(i,j))}{(1+C'_{\mu}(i,j))} & \mu(i,j) < \overline{\mu}_{w}(i,j) \end{cases}$$
(3.18)

Finally, a defuzzification process is adopted to obtain the enhancement result in the gray level domain. The enhanced intensity of pixel (i, j) is obtained by using the inverse function  $S^{-1}(\mu'(i, j); x, y, z)$ :

$$g'(i, j) = S^{-1}(\mu'(i, j); x, y, z)$$

$$= \begin{cases} g_{\min} + \frac{g_{\max} - g_{\min}}{z - x} \sqrt{\mu'(i, j) \times (y - x)(z - x)} & 0 \le \mu'(i, j) \le \frac{(y - x)}{(z - x)} \\ g_{\min} + \frac{g_{\max} - g_{\min}}{z - x} (z - x - \sqrt{(1 - \mu'(i, j) \times (z - y)(z - x)}) & \frac{(y - x)}{(z - x)} < \mu'(i, j) \le 1 \end{cases}$$
(3.19)

where  $g_{min}$  and  $g_{max}$  are the minimum gray level and maximum gray level after the enhancement.

# 3.2.6 Determination of the Amplification Exponent

The fuzzy entropy, En(i, j), is calculated and used to evaluate the uniformity

degree of the local region. The basic idea for determining the amplification exponent constant k(i, j) is this: If En(i, j) is low, the fuzzy membership of the region varies sharply, the degree of enhancement should be high, and the amplification exponent constant k(i, j) should be small. On the contrary, if En(i, j) is high, the fuzzy membership varies slowly, and k(i, j) should be large.

$$En(i, j) = -\frac{1}{\log_{10}(w \times w)} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} (\psi_w(m, n) \times \log_{10}(\psi_w(m, n)))$$
(3.20)

$$\psi_{w}(i,j) = \frac{E_{\mu}(i,j)}{\sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} E_{\mu}(m,n)}$$
(3.21)

$$E_{\mu}(i,j) = \mu(i,j) \times f_{\mu}(i,j) \times e_{\mu}(i,j)$$
(3.22)

The determination of the minimal and maximal amplification constants,  $k_{min}$  and  $k_{max}$ , should relate to the contrast of the original image. At first, the local contrast of the original image is computed. Next, some measurements of the contrast are calculated to evaluate the degree of the contrast of the original image.

The local contrast of the original image is computed in the gray level domain as follows:

$$C(i, j) = \left| g(i, j) - \overline{g}_{s}(i, j) \right| / \left| g(i, j) + \overline{g}_{s}(i, j) \right|$$
(3.23)

$$\overline{g}_{s}(i,j) = \frac{1}{s \times s} \sum_{m=i-(s-1)/2}^{i+(s-1)/2} \sum_{m=j-(s-1)/2}^{j+(s-1)/2} g(m,n)$$
(3.24)

where C(i, j) is the local contrast at pixel of (i, j), and  $\overline{g}_s(i, j)$  is the local mean of the gray levels in the window with size  $s \times s$  centered at pixel (i, j).

Then, the conditional mean value of the contrast  $\overline{C}_{R}$  is calculated.

$$\overline{C}_{R} = \frac{1}{M} \sum_{(i,j) \in G(R)}^{0 \le i \le H-1} \sum_{C(i,j) < R}^{0 \le j \le W-1} C(i,j)$$
(3.25)

where *H* and *w* are the height and width of the image, G(R) is the region having contrast value smaller than *R*, *M* is the number of pixels in this region, and  $\overline{C}_R$  is the mean value of the contrast whose values are smaller than *R*,  $R \in (0,1)$ . The method to determine *R* will be discussed later.

If we define the difference between the intensities of the central area and the overall image as  $\Delta L$  and the overall image intensity as L, the ratio between the two is called the Weber ratio w [96]:

$$W = \frac{\Delta L}{L} \tag{3.26}$$

If a region differs in intensity from its surroundings by less than 2% [96, 125], it is indistinguishable to the human eye. In order to increase the image contrast over the Weber ratio and accomplish the enhancement task, the contrast ratio,  $C_{\mu}(i, j)$ , which is less than 2%, should be transformed to  $C'_{\mu}(i, j)$  which is more than 2%. The aim of selecting  $k_{\text{max}}$  and  $k_{\text{min}}$  is to increase image contrast above the threshold. Therefore, we define R=0.02 as the Weber ratio [96, 125].

The maximal and minimal amplification exponent constants are determined as follows:

$$k_{\max} = \frac{\log R}{\log \overline{C}_R} \tag{3.27}$$

$$k_{\min} = \frac{\log R}{\log C_{\min}} \tag{3.28}$$

where  $\overline{C}_{R}$  is the mean value of the contrasts whose values are smaller than R, and  $C_{\min}$  is

the minimal value of the contrasts.

Finally, the local amplification exponent is obtained as:

$$k(i, j) = k_{\min} + \frac{(En(i, j) - En_{\min}) \times (k_{\max} - k_{\min})}{En_{\max} - En_{\min}}$$
(3.29)

where  $En_{min}$  are  $En_{max}$  the minimal and maximal local fuzzy entropy, respectively.

 $En_{\min} = \min_{i,j} \left\{ En(i,j) \right\}, \ En_{\max} = \max_{i,j} \left\{ En(i,j) \right\}.$ 

All steps of the algorithm are summarized in the flowchart in Figure 3.2.



Figure 3.2. The flowchart of the enhancement algorithm.
### **3.3 Experimental Results and Discussion**

# 3.3.1 Experiments on Breast Ultrasound Images

To test the proposed method, we applied it to five breast ultrasound images. The parameters of the algorithm for each image are listed in Table 3.1. Figures 3.3 through 3.7 show experimental results of the proposed method. Figures 3.3(a), 3.4(a), 3.5(a), 3.6(a), and 3.7(a) are the original images, and Figures 3.3(b) through 3.7(b) are the results obtained by using the proposed method, respectively. A mass's features, such as shape, edge, echo inside, are important criteria for distinguishing between malignancy and benignancy. After being enhanced by the proposed method, the lesions' features are significantly improved.

Figure 3.3(a) has a compact mass at the center of the image, and the mass echo and intensity are very low. The mass is hardly distinguishable from the background. In Figure 3.3(b), the mass becomes clearer and easier to detect, and the shape and edge can be better extracted.

Image	w size	s size	$k_{\min}$	k <sub>max</sub>
Figure 3.3	5x5	3x3	0.4299	0.8473
Figure 3.4	5x5	3x3	0.4023	0.8528
Figure 3.5	5x5	3x3	0.4700	0.8385
Figure 3.6	5x5	3x3	0.4472	0.8505
_				
Figure 3.7	5x5	3x3	0.4229	0.8634

Table 3.1. Parameters for the Images.



Figure 3.3. First example of breast ultrasound image enhancement. (a) Original image. (b) image enhanced by the proposed method.



Figure 3.4. Second example of breast ultrasound image enhancement. (a) Original image. (b) Image enhanced by the proposed method.



Figure 3.5. The third example of breast ultrasound image enhancement. (a) The original image (b) The image enhanced by the proposed method.



(a)



(b)

Figure 3.6. Fourth example of breast ultrasound image enhancement. (a) Original image (b) Image enhanced by the proposed method.



Figure 3.7. Fifth example of breast ultrasound image enhancement. (a) Original image (b) Image enhanced by the proposed method.

In Figure 3.4(a), the ill-defined border of the mass is almost invisible and not connected, especially, at the lower left. After applying the proposed method, the border is much clearer, and the structure surrounding the mass is more distinct.

Figure 3.5(a) has a loose cluster of microcalcifications at the center of the mass. In Figure 3.5(b), those tiny spots become brighter, the microcalcifications are more distinct. Meanwhile, the glandular tissue on the upper area is not over-enhanced.

Figure 3.6(a) has a different type of mass with a well-circumscribed border. The mass has a low echo inside, the intensity inside the mass is very low, and details cannot be seen clearly. After enhancement, not only is the boundary of the mass considerably improved, but also the structure inside the mass is sharper.

The mass in Figure 3.7(a)has a blurry edge, and the inside structures are barely distinguishable. The difference between the bottom of the mass and other tissues is very small. In the enhanced image, the mass can be distinguished from its surroundings, and the microcalcifications inside the mass are much clearer.

#### *3.3.2 Comparison with Other Methods*

In this section, the proposed method is compared with two enhancement methods: a modified histogram equalization method [114] and a fuzzy logic-based method [132].

In the diagnosis of breast cancer, a mass is regarded as an important criterion. Features of the mass playing a significant role in breast cancer diagnosis include shape, boundary, branch, internal structures, and the microcalcifications. The enhancement results of these regions determine the performance of the enhancement algorithm.

Figures 3.8 through 3.11 show comparisons of the proposed method with the modified histogram equalization method [114] and the fuzzy logic based method [132] on breast disease ultrasound image enhancement. Figures 3.8 and 3.9 are malignant images, and Figure 3.10 and 3.11 are benign cases. Figures 3.8(a), 3.9(a), 3.10(a), and 3.11(a) show the original image. Figures 3.8(b) through 3.11(b) show the enhancement results by the proposed approach. Figures 3.8(c) through 3.11(c) are the image enhanced by the modified histogram equalization method. Figures 3.8(d) through 3.11(d) provide the enhancement results by the fuzzy logic-based method. The white rectangles on the images highlight the important regions to be compared.

Figure 3.8(a) shows a mass with several branches. The shape and boundary of the branches are very useful for diagnosis. In Figure 3.8(b), the mass is clear and is easy to detected. Its boundary is distinct, and the shape easily described. In Figure 3.8(c), although the mass's edge is enhanced sharply, the inside structure of thatmass and gland region are over-enhanced, which is not suitable for diagnosis. The result in Figure 3.8(d) is under-enhanced, and the contrast is low.

In Figure 3.9, the central mass has several microcalcifications, which is another

important feature in judging ROIs. In Figure 3.9(a), these microcalcifications are very fuzzy. It is difficult to measure their position, size, shape and number. In Figure 3.10(b), the micorcalcifications are enhanced correctly, and the contrast is improved. It is easy to measure their position, size, shape, and number. In addition, over-enhancement does not occur. In Figure 3.10(c), the microcalcifications and structure inside the mass are over-enhanced. In Figure 3.10(d), these microcalcifications are not clear, not easy to detect.

Figures 3.10 and 3.11 show a distinct mass. The boundary of the mass is very smooth, which is diagnosed as a benign case. The up boundary of the mass in Figure 3.5(a) is very fuzzy. After enhancement, as shown in Figure 3.10(b), the up boundary becomes distinct, and the inside structure is enhanced correctly. Figures 3.10(c) and (d) are over-enhanced and under-enhanced, respectively. In Figure 3.11(a), the mass' boundary is very clear and smooth. As such, the structure inside the mass is very useful for doctors. Figures 3.11(b) and (d) show the mass enhanced correctly, and make the inside structure clearer. However, there are some over-enhanced regions in Figure 3.11(c).

A comparison of the experimental results shows that the proposed method achieves better performance than the modified histogram equalization method [114] and the fuzzy logic-based method [132]. The lesions' features in the breast ultrasound images are better enhanced, and all details are well preserved. In addition, over-enhancement is avoided. This better performance should prove useful for radiologist in diagnosing breast cancer.









(c)

(d)

Figure 3.8. First example of breast ultrasound image enhancement comparison. (a) Original image. (b) Enhanced image using the proposed method. (c) Enhanced image using the modified histogram equalization method. (d) Enhanced image using the fuzzy logic based method.





Figure 3.9. Second example of breast ultrasound image enhancement comparison. (a) Original image. (b) Enhanced image using the proposed method. (c) Enhanced image using the modified histogram equalization method. (d) Enhanced image using the fuzzy logic based method.



(c)

(d)

Figure 3.10. Third example of breast ultrasound image enhancement comparison. (a) Original image. (b) Enhanced image using the proposed method. (c) Enhanced image using the modified histogram equalization method. (d) Enhanced image using the fuzzy logic based method.



Figure 3.11. Fourth example of breast ultrasound image enhancement comparison. (a) Original image. (b) Enhanced image using the proposed method. (c) Enhanced image using the modified histogram equalization method. (d) Enhanced image using the fuzzy logic based method.

#### 3.3.3 Experiments on Clinical Breast Cancer Diagnoses

The proposed approach significantly enhances the contours and the fine details of ultrasound images. These enhanced images can be processed further to detect the tumors with high accuracy. Such enhancement is very useful for diagnosis.

In order to evaluate the performance on the diagnosis of proposed method, a comparative study of the diagnostic results of the ultrasologists was done with/without using the proposed enhancement algorithm. In all, 350 ultrasound images from 115 cases were analyzed including 59 benign and 56 malignant lesions. The original breast images were enhanced. The original and enhanced images were assessed and evaluated by ultrasologists using a double blind method before and after enhancement. The diagnostic sensitivity and specificity were calculated by the areas (Az) under the receiver operating characteristic (ROC) curves. The two diagnostic results of before and after enhancement were compared by the Chi-square test in a  $2 \times 2$  table. The results demonstrate that the discrimination rate of breast masses is highly improved after employing the novel enhancement algorithm. Sensitivity raised from 74.3% to 89.3% with the false-positive (FP) rate 14.3%, and the area (Az) under the ROC curve of diagnosis increased from 0.84 to 0.93. The proposed enhancement algorithm can, thus, increase the classification accuracy and decrease the rate of missing and misdiagnosis, making it useful for breast cancer detection.

The 350 original images were processed using the newly developed enhancement algorithm. The original images and enhanced images were randomly given to experienced ultrasologists who did not know the initial results. According to these ultrasound characteristics, the lesion was located, the margin feature was analyzed, and the ultrasound characteristics of the lesion were extracted. A benign or malignant classification was determined. The diagnostic results were divided into five categories: (1) definitely or almost definitely benign, (2) probably benign, (3) possibly benign/ malignant, (4) probably malignant, (5) definitely or almost definitely malignant.

The diagnostic results of ultrasologists on both the original and enhanced images were analyzed and assessed by ROC curves. The results before and after enhancement were tested by Chi-square test in a 2×2 table. The accuracy of the diagnosis was evaluated in terms of sensitivity (Se) and specificity (Sp). The accuracy of the two methods was determined by the area "Az" under the ROC curve ( $0 \le Az \le 1$ ). The closer to 1 the Az is, the better the diagnosis is. If Az =0.5, it acts as no effect, and if Az<0.5, it does not accord with reality.

The diagnostic results obtained by the ultrasologists using the original images and enhanced images and the pathological results are listed in Tables 3.2 and 3.3, respectively.

Ultrasound Pathology	Benign	Probably Benign	Possibly Benign/Malignant	Probably Malignant	Malignant	Total
Benign	28	8	14	5	4	59
Malignant	4	4	6	12	30	56

Table 3.2. Ultrasound Diagnostic and Pathological Results Based on the Original Images.

Table 3.3. Ultrasound Diagnostic and Pathological Results Based on the Enhanced Images.

Ultrasound Pathology	Benign	Probably Benign	Possibly Benign/Malignant	Probably Malignant	Malignant	Total
Benign	38	6	13	3	2	59
Malignant	2	2	3	8	41	56

The two tables show that breast lesions definitely diagnosed increased from 58 cases in the original images (30 malignant cases and 28 benign cases shown Table 3.2 ) to 79 cases in the enhanced images (41 malignant cases and 38 benign cases shown in Table 3.3), asignificant improvement.

At different cutoff values, the sensitivity and specificity of ultrasologists' diagnosis on the original and enhanced breast images indicate the following: when the false-positive rate is 14.3%, the sensitivity of the enhanced images improves from 74.3% to 89.3%, and when the false-positive rate is 35.7%, the sensitivity of the enhanced images also improves significantly from 83.9% to 96.4%.

The ROC curves of ultrasologists' diagnosis on the original and enhanced images are shown in Figure 3.12.



Figure 3.12. ROC curves of the original and enhanced breast ultrasound images.

From Figure 3.12, we see that the ROC curve of the ultrasologists' diagnosis on the enhanced images is more convex than that of the original images. This implies that the curve has a higher diagnostic value. Using the ROC curve, the ranges of the areas are calculated: the original images Az1=0.84, and its 95% credible interval is [0.734, 0.950]. While the enhanced images Az2=0.93, its 95% credible interval is [0.862, 1]. From this, we can conclude that the enhanced images have an improved accuracy rate of diagnosis.

#### **3.4 Conclusions**

A breast ultrasound image enhancement algorithm based on fuzzy logic and fuzzy homogeneity was developed. The proposed method is very efficient and effective in contrast enhancement: (1) The lesions' features in breast ultrasound images are better enhanced, and all details are well preserved. (2) Over-enhancement is avoided. This good performance is due to the following factors: (1) The S function is used in image fuzzification, and the parameters are determined using the fuzzy entropy theory automatically. (2) The algorithm uses both local and global information. Therefore, the proposed approach is useful for breast ultrasound image analysis and CAD systems.

## **CHAPTER 4**

# BREAST ULTRASOUND IMAGE SEGMENTATION

Computer aided diagnosis (CAD) system will help radiologists in reading and interpreting sonography. Segmentation is an important step in image processing, which divides an image into non-overlapping regions. It is essential and critical to detecting lesions and making correct diagnoses.

# 4.1 Summary of Breast Ultrasound Image Segmentation

### 4.1.1 Histogram Thresholding Method

Many algorithms have been proposed for segmenting BUS images. The authors of [133, 134] discuss a segmentation algorithm for masses on sonography using the following steps: (1) preprocessing using cropping and median filtering, (2) multiplying the preprocessed image with a Gaussian constrain function, (3) determining the potential lesion margins through gray-value thresholding, and, (4) maximizing a utility function for the potential lesion margins. However, the center, the width, and height of the lesions are selected manually or semi-manually. A radial gradient index (RGI) filtering technique [135] was used to segment and detect lesions in BUS images. After ROIs are located by the RGI filtering technique and their centers are documented as points of interest, a region-growing algorithm is used to determine candidate lesion margins. The lesion candidates are segmented by maximizing an average radial gradient (ARD) index for region growing. However, the algorithm does not perform well if the lesion is not compact and round-like. A segmentation algorithm for breast lesions based on multi-

resolution texture adaptive clustering has been proposed [136]. This algorithm improves on the one proposed in [137] by including the energy function to measure the textural properties of various kinds of tissues. The algorithm involves 2D adaptive K-means clustering. The segmentation problem is formulated as a maximum a posteriori (MAP) estimation problem. The MAP estimation utilized Besag's iterated conditional mode for minimizing an energy function, constraining the region close to the data, imposing spatial continuity, and considering the textural information of various regions. However, the input images for this algorithm are only ROIs.

In summary, histogram thresholding methods tend to be less effective for images with a nonbimodel histogram. In addition, some of them are sensitive to noise and contrast. The speckles, weak edges and tissue-related textures in BUS images prevent determination of the tumor boundaries satisfactorily.

#### 4.1.2 Active Contour Model

Some segmentation algorithms have been proposed based on the active contour model. The 3D active contour model is applied to a 3D ultrasonic data file for segmenting a breast tumor [138, 139]. A 3D stick is used to handle ultrasonic images with speckle noise and to highlight the edges. Then, a 3D morphologic process helps in determining the contour of the tumor and the initial assignment of the active contour model. Finally, the 3D active contour model is used to locate the real contour of the tumor. The input images for the algorithm are only ROIs selected by radiologists. A segmentation algorithm was proposed [140, 141]. It has four steps. First, the ROIs are preprocessed with a 4 ×4 median filter to reduce the speckle noise and to enhance the features. Second, a 3 ×3 unsharp filter is constructed using the negative of a 2D Laplacian filter to

emphasize the elements with meaningful signal levels and to enhance the contrast between nodule and background. Third, the ROIs are converted to a binary image by thresholding. The threshold is determined by the histograms of ROIs. If a valley of the histogram between 33% and 66% of the pixel population can be found, this intensity value is selected as the threshold. If no such a valley in that range exists, the intensity of the 50% pixel population is selected as the threshold. The selected nodule's boundary pixels are obtained using morphologic operations. The algorithm only can handle the ROIs, and threshold selection relies on the shape of the histogram and the intensity distributions of ROIs.

The 3D snake technique has been used to obtain a tumor contour for pre-operative and post-operative malignant breast excision [138]. By using anisotropic diffusion filter, the noise and speckle are reduced. The stick detection is next adopted for enhancing the edge. Finally, the gradient vector flow (GVF) snake is used to locate the tumor contour. However, the automatic threshold method is too simple and primitive and does not perform well for unimodal histograms [142].

Methods based on a snake deformation model can only handle ROIs, not the entire image. The accuracy of the snake deformation process depends on the initial estimation of the contours [143, 144]. Automatically generating a suitable initial contour is very difficult, and the snake-deformation process is very time consuming.

# 4.1.3 Neural Networks

A study [145] integrated neural network (NN) classification and morphological watershed segmentation to extract the contours of the breast tumors. In the study, textural analysis is employed to find the inputs for the NN to classify ultrasonic images.

Watershed transformation automatically determines the contour of the tumor. Selecting the training set is problematic, and training an NN is time-consuming and depends on the image database. One algorithm [146] combined expectation maximization (EM) with hyper-parameter estimation and MPM (maximization of posterior marginal), and extended the EM/MPM framework to 3D by including pixels from neighboring frames in the Markov random field (MRF) clique. However, there are many noisy spots in the segmentation results, and the algorithm is time-consuming. A technique to automatically find lesion margins that combined intensity and texture with empirical domain-specific knowledge with gradient and a deformable shape-based model has been presented [147]. Images are first filtered to remove speckle noise, and contrasts are enhanced. The empirical rules for detecting ultrasonic breast lesions by radiologists are employed to automatically determine a seed point in the image. This is followed by region growing to obtain an initial segmentation of the lesion, and pixels are classified based on intensity and texture. Boundary points are found on the directional gradient of the image, which are utilized as the initial estimate of a deformable model.

BUS images suffer from speckle noise due to interference from back-scattered signal, and such noise significantly degrades image quality and hinders the discrimination of fine details. BUS images have fuzziness, such as indistinct cyst borders, ill-defined mass shapes, blurry tumor boundaries, etc., making segmenting BUS images automatically and correctly difficult. Furthermore, some of above methods only use ROIs and cannot be used on CAD systems. In addition, many of these methods do not take into consideration of the characteristics of BUS images [148].

Method	Description	Advantage	Disadvantage
Histogram	The threshold value is	Simple and fast.	Less effective for images
thresholding	selected to segment the		with nonbimodel
method	image.		histogram.
Active	Snake-deformation	It can extract lesions	Slow iteration speed.
contour	mode is utilized to	with different shapes	
model	extract the lesion on	and keep the	
	ultrasound images.	boundary correct.	
Neural network (NN)	Segmentation is regarded as a classification problem, which is solved by NN.	It extracts the contours of tumors automatically.	Select the training set is problematic, and training a NN is time-consuming and dependent on the image database.

Table 4.1. Breast Ultrasound Image Segmentation Methods [34].

# 4.2 Proposed Method

This chapter proposes a novel automatic segmentation algorithm, which not only employs the entire image for segmentation, but also utilizes BUS image characteristics. Our method is employed to extract the mammary gland area. Furthermore, a new eliminating particle swarm optimization (EPSO) clustering algorithm is proposed based on the idea of "survival of the superior and weeding out the inferior" to segment the BUS images quickly and accurately.

The particle swarm optimization (PSO) algorithm is an evolutionary computation technique utilizing random searching inspired by the mechanisms of natural selection and genetics to emulate the evolutionary behaviors of biological systems. PSO has a fitness evaluation function to compute each position's fitness value. The position with the highest fitness value in the entire run is called the global best solution  $P_{Best}$ . Each particle tracks its highest fitness value. The location of this value is called the personal best solution  $P_i$ . The algorithm involves casting a population of particles over the search space

and remembering the best solution encountered. On each iteration, every particle adjusts its velocity vector based on its momentum, and the effect of both its best solution and the global best solution of its neighbors. Studies show that the PSO has more chances to "fly" into better solution areas quickly; hence, it can discover a reasonable solution much faster than other evolutionary algorithms.

Our modified PSO, called eliminating PSO (EPSO), is based on the idea of "survival of the superior and weeding out the inferior." N particles whose velocities and positions are updated accordingly are initialized, and the positions' fitness values are calculated and sorted in a list in descending order. Then, L particles whose fitness values are in the last L positions of the list are eliminated. This reduces the computational time, while the accuracy of the solution is not affected. The process iterates until the maximum iteration number is reached or the minimum error condition is satisfied.

EPSO clustering is an algorithm based on k-means clustering and the EPSO algorithm. The centers of the clusters are considered as the particle's positions, and the EPSO algorithm is employed to search the optimum solution by eliminating the "weakest" particles to speed up the computation. K-means clustering is utilized to update the positions of particles.

When the EPSO clustering algorithm is applied to ultrasound image segmentation, the intensities of pixels are the input to the EPSO clustering algorithm, and the pixels are grouped according to the optimum centers of EPSO clustering.

BUS images have some fuzziness including vague tumor boundaries, high amount of speckles, low contrast between suspicious area and breast tissues, etc. Therefore, it is necessary to suppress speckle noise before segmentation.

#### 4.2.1 Speckle Reduction

Speckle noise is inherent in US imaging, and tends to reduce the resolution and contrast, thereby, diminishing diagnostic accuracy. In order to remove speckle noise, we implement an algorithm for speckle reduction based on 2D homogeneity histogram (homogram) [149] and directional average filters discussed in chapter 2. After speckles in the BUS image are removed, the regions become more homogeneous and the boundaries of the regions much clearer, which is better for segmentation.

In this section, the structure of the BUS images is considered. Most breast cancers take in the mammary gland region. Therefore, it is significant to find the mammary gland region at first.

## 4.2.2 Mammary Gland Region Extraction

There are four layers of a BUS image [150]: skin, subcutaneous tissue, mammary gland and muscle. The boundaries between these layers are quite blurry, as shown in Figure 4.1.

This section proposes a method based on the step-down threshold technique, which selects a threshold in each step, to extract the mammary gland area from the entire image. The mammary gland region is located between the subcutaneous tissues and muscle layers, which are characterized as a line-like area with high gray levels. The regions with high gray levels are searched to locate the layers of subcutaneous tissues and the chest muscle. After the layers of subcutaneous tissue and muscle are determined, the mammary gland region's top and bottom margins are detected, and the mammary gland region is extracted between the two margins.



Figure 4.1. Breast structure in an ultrasound image.

# 4.2.2.1 Thresholding the Image

A threshold value Th(m) is used to transform the BUS image into a binary image:

$$bw^{m}(i,j) = \begin{cases} 0 & \tilde{g}(i,j) \le Th(m) \\ 255 & otherwise \end{cases}$$
(4.1)

where  $\tilde{g}(i, j)$  is the gray level of P(i, j) after speckle reduction, Th(m) is the *mth* stepdown threshold value, and  $bw^m(i, j)$  is the binary image after the *mth* thresholding processing. How to determine Th(m) will be discussed later.

Next, we search the white region on the binary image. After the white regions  $\operatorname{Re}W(n)$  are found, the regions connected with the top and bottom margins are eliminated.

# 4.2.2.2 Detecting SubcutaneousTissues and Chest Muscle Regions

Because the subcutaneous tissues margin and muscle lines have high gray levels, the subcutaneous tissues margin and muscle line region can be located among the white regions obtained. The value of Ra, a ratio between the width and height, is used to eliminate the false subcutaneous tissues and muscle region:

$$Ra(n) = max(RaWH(n)) \tag{4.2}$$

$$RaWH(n) = \frac{W(n)}{H(n)}$$
(4.3)

where RaWH(n) is the ratio between the width and height of the *nth* candidate white region ReW(n).

The white region with a large enough width (more than 50% of the width of the entire image in our experiments) is regarded as the true subcutaneous tissue margin and muscle line. If the true subcutaneous tissues margin and muscle line are not found, the threshold value is updated, and the procedure is repeated. Otherwise, the iteration processing is terminated, and the muscle line is located to extract the mammary gland region in the next step. The threshold value of each step is updated:

$$Th(m+1) = \begin{cases} Th(m) - \Delta Th & m > 0\\ & & \\ 1 \le j \le W \\ 0.8 \times \max_{\substack{1 \le i \le H \\ 1 \le i \le H}} (\tilde{g}(i, j)) & m = 0 \end{cases}$$
(4.4)

where Th(m) and Th(m+1) are the *mth* and (m+1)th threshold values, respectively.  $\Delta Th$  is the decrement. Here,  $\Delta Th = 0.1 \times \max_{\substack{1 \le j \le W \\ 1 \le i \le H}} (\tilde{g}(i, j))$ .

#### 4.2.2.3 Extracting the Mammary Gland Region

The subcutaneous tissue margin and chest muscle line detected above are the top and bottom margins of the mammary gland region. The region is extracted successfully from the subcutaneous tissue and muscle layer. A flowchart of mammary gland region extraction method is shown in Figure 4.2.

### 4.2.3 Mammary Gland Image Enhancement

Breast ultrasound images have low contrast and some degree of fuzziness such as indistinct cyst borders, ill-defined mass shapes, and different tumor densities. Image enhancement is used to improve the quality of the image and to correct deficiencies of the contrast. We implement an algorithm for mammary gland image enhancement based on fuzzy logic, which is described in Chapter 3. After the mammary gland images are enhanced, the contrast is improved and the boundaries of the regions much distinct, which is better for segmentation.

# 4.2.4 Mammary Gland Image Segmentation

After preprocessing, the mammary gland region is extracted, and the lesions become more distinct. This chapter proposes a method combined with eliminating particle swarm optimization (EPSO) algorithm and k-means clustering to segment the mammary gland regions. In the proposed segmentation method, a k-means clustering result is employed to optimize the position of each particle in the swarm.



Figure 4.2. Flowchart of mammary gland region extraction algorithm.

### 4.2.4.1 Clustering Analysis

Clustering analysis can classify similar points into the same group [151, 152]. Let  $X = \{X_i, i = 1, 2, \dots, n\}$  be a data set, and  $x_i$  be a point in the d-dimensional space. The problem of clustering is to find a partition  $C = \{C_1, C_2, \dots, C_m\}$ , which satisfies:

$$X = \bigcup_{i=1}^{m} C_{i}$$

$$C_{i} \neq \Phi \quad \text{for } i=1,2,\cdots, m$$

$$C_{i} \cap C_{i} = \Phi \quad \text{for } i,j=1,2,\cdots, m; i \neq j$$

$$(4.5)$$

The K-means algorithm is a widely used clustering analysis algorithm [153], whose objective function is defined as:

$$J_{c} = \sum_{j=1}^{m} \sum_{i=1}^{n_{j}} \left\| X_{i} - Z_{j} \right\|$$
(4.6)

where  $z_j$  is the center of the  $j^{\text{th}}$  cluster, *m* is the number of clusters and  $n_j$  is the number of pixels in the  $j^{\text{th}}$  cluster:

$$Z_{j} = \frac{1}{n_{j}} \sum_{X_{i} \in C_{j}} X_{i}$$

$$(4.7)$$

where  $n_i$  is the number of the elements in cluster  $C_i$ .

# 4.2.4.2 Eliminating Particle Swarm Optimization Algorithm

The particle swarm optimization (PSO) algorithm is an evolutionary computation technique utilizing a random search inspired by the mechanisms of natural selection and genetics to emulate the evolutionary behaviors of biological systems. As introduced in [154], PSO simulates simplified swarm social models such as birds flocking or fish schooling.

PSO has a fitness evaluation function to compute each position's fitness value.

The position with the highest fitness value in the entire run is called the global best solution  $P_{\text{Best}}$ . Each particle tracks its highest fitness value. The location of this value is called the personal best solution  $P_i$ . The algorithm involves casting a population of particles over the search space and remembering the best solution encountered. At each iteration, every particle adjusts its velocity vector based on its momentum and the effect of both its best solution and the global best solution on its neighbors. It then selects a new point to examine. Studies have shown that PSO has more chances to "fly" into better solution areas quickly; hence, it can discover a reasonable solution much faster than other evolutionary algorithms. The PSO formulation is described in [154, 155].

Let  $P_i$  represent the *i*<sup>th</sup> particle, whose position and velocity in a d-dimensional space are defined as  $x_{id}$  and  $v_{id}$ , respectively. The position and velocity are updated according to the following formulas:

$$V_{id}(t) = \omega V_{id}(t-1) + c_1 rand()(P_{id}(t-1) - X_i(t-1)) + c_2 rand()(P_{ig}(t-1) - X_i(t-1))$$
(4.8)

$$X_{id}(t) = X_{id}(t-1) + V_{id}(t-1)$$
(4.9)

where  $x_{id}(t)$  is the position of the *i*<sup>th</sup> particle in a d-dimensional space at time step t,  $v_i$  is the velocity of  $P_i(t)$ .  $P_{id}$  and  $P_{ig}$  represent the *d*<sup>th</sup> and *g*<sup>th</sup> position of the *i*<sup>th</sup> particle. Parameters  $c_1$  and  $c_2$  are learning factors,  $c_1 = c_2 = 2$ .  $\omega$  is an inertia weight,  $\omega = 0.1$ , and *rand*() is a function to generate a random variable.

A modified PSO, eliminating PSO (EPSO), is based on the idea of "survival of the superior and weeding out the inferior." N particles whose velocities and positions are updated accordingly are initialize, and the positions' fitness values are calculated and sorted in a list in descending order. Next, L particles whose fitness values are in the last L positions of the list are eliminated. This reduces computational time, while the accuracy

of the solution is not affected. The process is iterated until the maximum iteration number is reached or the minimum error condition is satisfied.

EPSO clustering is an algorithm based on k-means clustering and the EPSO algorithm. The centers of the clusters are considered as the particles positions, EPSO is employed to search the optimum solution by eliminating the "weakest" particles to speed up computation. K-means clustering is utilized to update the positions of particles.

The procedure of clustering analysis based on EPSO and k-means clustering is described below:

- (1) Select *M* particles (primary population number), and put them into the primary swarm  $S(1) = \{P_1, P_1, \dots, P_M\}$ , and initialize the positions  $X_{id}$  of swarm *s* using k-means clustering results;
- (2) Randomly initialize the velocities  $V_{id}$ ;
- (3) Evaluate the fitness of each particle  $Fit(X_{id}(t))$ ;
- (4) Compare the personal best of each particle in the new swarm s(t+1) with its current fitness value, and set  $P_{id}(t)$  to the better performance.

 $P_{id}(t+1) = \begin{cases} P_{id}(t) & Fit(P_{id}(t)) > Fit(X_{id}(t)) \\ X_{id}(t) & Fit(P_{id}(t)) \le Fit(X_{id}(t)) \end{cases}$ 

- (5) Set the global best  $P_{gd}(t+1)$  to the position of the particle with the best fitness in the swarm;
- (6) Sort the particles according to the fitness values. A new swarm s(t+1) is obtained by eliminating the *L* particles whose fitness values are in the last *L* positions of the list;
- (7) Optimize the position of each particle in the new swarm S(t+1) according to k-

means clustering principle;

- (8) Change the velocity vector  $V_{id}(t+1)$  for each particle according to Eq. (27);
- (9) Update each particle position in S(t+1);
- (10) Go to step (3), and repeat the process until the maximum iteration number or the minimum error is reached.

## 4.2.4.3 Mammary Gland Image Segmentation

The EPSO clustering algorithm is applied to mammary gland image segmentation. The pixels' intensities are the inputs of the EPSO clustering algorithm, and the pixels are grouped according to the optimum centers of EPSO clustering. In the proposed method, based on experimental results, N is initialized to be 65, and L is 5. Because the intensities of the pixels belonging to a lesion are very low, the group of pixels with the lowest intensities can be regarded the lesion-like pixels. The mammary gland region is located by the following formula:

$$bw(i, j) = \begin{cases} 0 & g(i, j) \in C_1 \\ 255 & otherwise \end{cases}$$
(4.10)

where g(i, j) is the pixel in mammary gland region at the location (i, j), and  $C_1$  is the cluster with the lowest intensities. *bw* is the binary mammary gland image after segmentation.

After the mammary gland is segmented, the round-like regions are reserved as the lesion-like regions and others are eliminated. The steps of the complete segmentation algorithm are shown in Figure 4.3.



Figure 4.3. Flowchart of the breast ultrasound image segmentation algorithm.

### 4.3 Experimental Results and Discussion

The proposed segmentation method was tested on timages in the breast ultrasound images database described in Chapter 2. Here, experimental results are presented to demonstrate the performance of the proposed method.

Figures 4.4(a), 4.5(a), and 4.6(a) are the original BUS images, in which most of the bright areas are the breast and muscle tissues, and the suspicious tumor areas are corrupted by speckle noise. Figures 4.4(b) through 4.6(b) are the segmentation results by experts. Figures 4.4(c) through 4.6(c) are the results after speckle reduction. Figures 4.4(d) through 4.6(d) show the mammary gland regions extracted from Figures 4.4(c) to 4.6(c). As can be seen from the images, after speckle reduction and enhancement, noise is removed while the edges are preserved, and the contrast between the background and suspected areas is greatly enhanced. Figures 4.4(e) through 4.6(e) are the enhancement results of mammary gland images, and Figures 4.4(f) through 4.6(f) are the segmentation results by the proposed approach. We compare the segmentation results with those of the method without speckle reduction and enhancement, which are shown in Figures 4.4(g) through 4.6(g).

In Figure 4.4, an oval mass is corrupted by speckle noise. In Figure 4.4(f), the mass is segmented correctly, and the edge is distinct, which is more suitable for mass detection and classification.

Figure 4.5(a) has a lesion with some branches at the center, which are an important indication in breast cancer diagnosis. In Figure 4.5(f), the mass and its branches are segmented correctly.

Figure 4.6(a) displays a lesion with an ill-defined border. The segmentation result

in Figure 4.6(f) shows that the lesion border's integrity is preserved well.

The experiments demonstrate that the proposed algorithm performs well on BUS images with speckle noise, and segments lesions correctly. The proposed segmentation algorithm is less sensitive to noise because of the utilization of an effective speckle reduction algorithm. Furthermore, the EPSO clustering method reduces the computational time by 32.75% compared with the standard PSO clustering algorithm. EPSO clustering was implemented using Matlab 7.1, and the program was executed on a PC with a single processing unit Intel Pentium IV 3.0GHz and 1GMB random access memory. The average execution time was 157 second per image with an average size of 500X600, while the average execution time using the conventional PSO clustering algorithm was 233 second per image. After segmentation, lesions can be detected and classified easier and better.

A universally accepted objective criterion of the performance of segmentation algorithms does not yet exist. The match rate (MR) between the manually determined areas and the automatically located lesions by the proposed algorithm is used to quantitatively evaluate the performance of the proposed algorithm. The MR is defined as:

$$MR = \frac{A_m \cap A_a}{A_m} \tag{4.11}$$

where  $A_m$  is the area of the tumor determined manually by radiologists and  $A_a$  is the area of the lesion determined automatically by the proposed algorithm. In our experiments on the 30 images, the average match rate of the proposed algorithm was 0.9627. The values of MR of Figures 4.4 through 4.6 are shown in Table 4.2.



(d)

(a)

(b)



(e)



Figure 4.4. First example of breast ultrasound image segmentation. (a) Original image. (b) Expert segmentation. (c) Image after speckle reduction. (d) Extracted mammary gland image. (e) Enhanced mammary gland image. (f) Segmentation result. (g) Segmentation result without speckle reduction and enhancement.







(d)

(f)

(e)



(g)

Figure 4.5. Second example of breast ultrasound image segmentation. (a) Original image. (b) Expert segmentation. (c) Image after speckle reduction. (d) Extracted mammary gland image. (e) Enhanced mammary gland image. (f) Segmentation result. (g) Segmentation result without speckle reduction and enhancement.





Figure 4.6. Third example of breast ultrasound image segmentation. (a) Original image. (b) Expert segmentation. (c) Image after speckle reduction. (d) Extracted mammary gland image. (e) Enhanced mammary gland image. (f) Segmentation result. (g) Segmentation result without speckle reduction and enhancement.

Image	MR of the proposed method	MR of the proposed method without speckle reduction and enhancement
Figure 4.4	0.9543	0.8932
Figure 4.5	0.9842	0.9553
Figure 4.6	0.9584	0.8784

# **4.4 Conclusion**

Breast cancer is one of the most common cancers and is a leading cause of death among women. The automated segmentation of BUS images is an essential issue for CAD systems. However, most existing algorithms are only for segmenting ROIs. In this dissertation, a BUS image segmentation algorithm based on EPSO clustering is proposed. The major advantage of the proposed algorithm is that it can handle the entire image automatically and accurately instead of focusing exclusively on ROIs, since it utilizes the characteristics of mammary gland of the BUS images. Also, the algorithm has very low computational time and complexity. The proposed approach may find wide applications in automatic lesion classification and CAD systems for breast cancer detection.
#### CHAPTER 5

#### CONCLUSION

Medical imaging plays a significant role in medical diagnosis. This dissertation aims to improve the accuracy of computer-aided detections system in ultrasound imaging. Medical ultrasound imaging is a key tool in medical diagnosis.

Using breast ultrasound image characteristics as a touchstone, this dissertation proposes three algorithms: image speckle noise reduction, breast ultrasound image enhancement, and breast ultrasound image segmentation, which are all applied to breast cancer computer-aided detection. The primary innovations contained herein are as follows:

- 1. To deal with speckle noise in the medical ultrasound image, this dissertation proposes a novel approach for speckle reduction using 2D homogeneity and directional average filters to remove speckle noise in an ultrasound image. The algorithm uses texture information to describe the speckle noise of ultrasound images, and ultrasound image is transformed from a gray level domain to a homogeneity domain. The speckle noise is removed by a new directional filter operation. Experiments show that this method can effectively reduce noise while still preserving details. This algorithm can be applied to preprocessing in CAD systems and achieves a better performance on speckle reduction than other methods.
- 2. To deal with the low contrast and fuzzy nature of breast ultrasound images, this dissertation proposes a novel breast ultrasound image enhancement algorithm based on fuzzy logic, which not only takes into account global

information, but also uses local information: fuzzy domains edge and texture information. Clinical experiments show that the features of an image, such as mass, microcalcification, internal echo, etc. are well enhanced. In addition, over-enhancement and under-enhancement are avoided. The algorithm is of great significance to improving the accuracy of breast cancer diagnosis.

3. Image segmentation is an important step for computer-aided detection. Medical ultrasound images have inherent speckle noise, and human tissue texture feature makes segmentation more difficult. Using characteristics of breast images as well as the structure of breast tissue as a touchstone, this dissertation proposes an eliminating particle swarm optimization (EPSO) clustering analysis, which transform segmentation problem into clustering analysis. Its advantage is to handle the entire image without manual selecting ROIs. It significantly reduces the diagnostician's workload, and achieves automatic breast cancer detection. In addition, it can greatly improve the accuracy of tumor detection. The segmentation result is very useful for doctors in making diagnoses. In addition, compared with the traditional particle swarm algorithm, this algorithm reduces the number of particles, and the computation time.

In summary, this study successfully solved three important computer-aided detection problems by systematically developing medical image preprocessing methods that can be improve images' quality and aid doctors in detecting tumors on images.

The complexity of computer-aided detection of breast cancer has presented a great challenge to ultrasound image processing algorithms, which leaves much space for further research. Although this dissertation has made some progress on computer-aided detection, there are many aspects need to be studied in the future in order to achieve better performance and accuracy. Future research will focus on improving and extending existing methods and application to clinical practice, while closely tracking the new technologies for disease detection and diagnosis. The future works for this dissertation are described as follows:

- The enhancement algorithm is evaluated using clinical trials, which has a certain subjective. How to evaluate an enhancement algorithm need to be studied.
- 2. This segmentation method should be studied more, and more features of ultrasound image and characteristics of breast tissue should be considered and employed in future study. In addition, more effective rules should be studied to detect the true lesion regions and eliminate the non-lesion regions.
- 3. This dissertation only deals with the B mode ultrasound images, which are two dimensional gray-scale images. Three dimensional ultrasound images and Doppler ultrasound are widely used recently. The further research will extend the current algorithms to these new images.

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- [155] Eberhart, R.C. and Shi, Y. Particle swarm optimization: Developments, applications and resources. In *Proceedings of Congress on Evolutionary Computation*, 2001, 81-86.

# CURRICULUM VITAE

# Yanhui Guo

(April, 2010)

# **EDUCATION**

PhD, Computer Science08/2007-05/2010Utah State University, Logan, Utah, USAAdvisor: Dr. Heng-Da ChengDissertation: "Key Researches on Breast Cancer Computer Aided Detection inUltrasound Images"

MS, Computer Science 09/2000-07/2002 Harbin Institute of Technology, Harbin, Heilongjiang, China Advisor: Dr. Xianglong Tang Thesis: "Document Layout Analysis Based on Mathematical Morphology and Search Algorithm"

BS, Automation09/1995-07/1999Zhengzhou University, Zhengzhou, Henan, ChinaAdvisor: Dr. Zhongyong WangUndergraduate thesis: "Differential GPS and its Applications"

# **RESEARCH INTERESTS**

Image Processing Optical Character Recognition Pattern Recognition Artificial Intelligence Medical Image Processing Chinese Handwriting Character Recognition Computer Vision

# **RESEARCH AND WORK EXPERIENCE**

# **Research Assistant**

Image Processing, Pattern Recognition and Computer Vision (IPPRCV) Group, Department of Computer Science, Utah State University, Logan, UT

08/2007-present

- Research on medical image processing
  - Developed breast ultrasound image enhancement, speckle reduction and segmentation algorithms
  - Developed computer aided diagnostic system for distal radius fracture based on X-ray images with University of Toronto, Ontario, Canada
  - Developed algorithms to color cell image enhancement, and MRI image enhancement
  - Constructed a breast ultrasound image database to academic community
- Research on image processing and analysis
  - Proposed neutrosophic image processing algorithms, such as neutrosophic image thresholding, neutrosophic image denoise and neutrosophic image segmentation
  - > Developed the road crack detection system
- Research on Particle Swarm Intelligence algorithm
  - Proposed Eliminating Particle Swarm Optimization (EPSO) algorithm
  - > Improved random Hough transformation algorithm based on EPSO algorithm
  - > Developed breast ultrasound image segmentation based on EPSO algorithm
- Participation in the project Road Information Intelligent Detection System
  - Designed and implemented the road image acquisition system framework, including camera configuration, image grabbing card programming, GPS receiver programming, etc.
  - Developed the road image crack detection algorithms using Visual Studio 2005, including image thresholding, crack detection and classification, road information summary, etc.
- Participation in the project *Fingerprint Image Preprocessing* 
  - > Improved the quality of fingerprint images using image processing algorithms

Journal and Conference Reviewer	04/2003—present
• Act as a reviewer for several international journals and	conferences
<u>Journals</u>	
Reviewed papers for IEEE Transaction	09/2009-present
on Image Processing	
Reviewed papers for New Mathematics	07/2009—present
and Natural Computation	
Reviewed papers for IEEE Transaction	04/2008-present
on Signal Processing	
Reviewed papers for Pattern Recognition	10/2007-present

Reviewed papers for International Journal	04/2005—present
of Computing and Information Sciences (IJCIS)	
Conferences	
Reviewed papers for the 7th Joint Conference on	05/2003
Information Science on Computer Vision,	
Pattern Recognition and Image Processing	
Reviewed papers for Geometric Modeling and Imaging,	04/2005
2005. GMAI '05, IEEE	
Reviewed papers for Computer Graphics, Imaging	04/2005
and Visualization, 2007. CGIV '07, IEEE	
Reviewed papers for the 8th Joint Conference on	05/2005
Information Science on Computer Vision,	
Pattern Recognition and Image Processing	
Reviewed papers for the 11th Joint Conference on	11/2008
Information Science on Computer Vision,	
Pattern Recognition and Image Processing	

#### **Network Manager**

12/2008-04/2009

Department of Economic and Finance, and Department of Applied Economics, Utah State University, Logan, UT

• Maintained the network, servers and computers for faculties, staff and graduate students in two departments, including domain server configuration and maintenance, email server configuration and maintenance, domain user management, network design, software configuration, etc.

# **Research Assistant**

08/2000-07/2007

Pattern Recognition Research Center, School of Computer Science and Technology, Harbin Institute of Technology, Harbin, Heilongjiang, China

- Research on Breast Cancer Diagnosis Based on Ultrasound Image, supported by National Science Foundation of China, grant numbers: 60573071 and 30670546.
  - Developed breast ultrasound images enhancement, speckle reduction and segmentation algorithms
  - Developed breast cancer early diagnosis method based on fuzzy logic and ultrasound imaging, cooperating with Harbin Medical University, Harbin, Heilongjiang, China.
- Research on Breast Cancer Auto Detection Based on Mammograph, supported by the

Multidisciline Scientific Research Foundation of Harbin Institute of Technology, contract number: HIT. MD 2002.27

- > Developed image enhancement algorithm for mass detection on mammograph
- Research on document layout analysis, Chinese character recognition.
  - > Developed Chinese document layout analysis algorithm
  - > Developed Japan business card layout analysis algorithm
  - Developed printed digits recognition algorithm
  - Developed Chinese handwriting digits recognition algorithm
- Participation in the project *Business Bill Recognition and Checking System* with Beijing Northking Technology Company, Beijing, China.
  - > Designed and implemented bill image layout analysis system
  - > Designed and implemented bill image classification system
  - Improved printing Chinese character and digits recognition algorithms
- Participation in the project *Train Wheel Flaw Auto Detection System* 
  - > Extraction of the spring region of the train wheel
  - > Combined multiple classifiers to detect the flaw in the spring
- Participation in the project Japan Business Card Recognition System
  - > Designed and implemented Japan business card image layout analysis system
  - Designed and implemented Japanese Character Recognition system, such as text line segmentation, Japanese Character segmentation, etc.
- Participation in the project *Chinese Handwriting Digits Number Recognition System* with Yinhe Technology Company, Harbin, Heilongjiang, China.

#### **Research Assistant**

Department of Electrical Engineering, Zhengzhou University, Zhengzhou, Henan, China

• Worked on the project *Differential GPS and its Applications*.

# **TEACHING EXPERIENCE**

## **Teaching Assistant**

Department of Computer Science, Utah State University, Logan, UT

- Collaborated on class development, met with students upon request, and graded all assignments and programming projects.
  - ➢ Introduction to Computer Science—CS 1 (CS1400)
    Fall, 2009
  - ➢ Introduction to Computer Science—CS 2 (CS1410)
    Fall, 2009
  - Operating Systems and Concurrency (CS3100)
    Fall, 2009

# 12/1998-07/1999

09/2007—present

$\triangleright$	Advanced Computer Vision, Pattern Recognition	Spring, 2009
	and Image Processing (CS7650)	
$\triangleright$	Computer Systems Organization and Architecture II (CS3810)	Spring, 2009
$\triangleright$	Computer Organization (CS2550)	Spring, 2008
۶	Fuzzy Logic and Applications (CS6630)	Fall, 2007, 2008

## **Teaching Assistant**

09/2003-02/2005 School of Software, Harbin Institute of Technology, Harbin, Heilongjiang, China.

Teaching four experiment courses: Computer Introduction, C Program, Computer Network, and Data Structure.

# Instructor

# 02/2001-07/2001

School of Continuing Education, Harbin Institute of Technology, Harbin, Heilongjiang, China.

Teaching the course "Chinese Information Processing". ۲

# AWARDS AND HONORS

•	Excellent Graduate Student, Harbin Institute of Technology.	2002
•	Scholarships for Outstanding Students, Second Prize,	1995,1998
	Zhengzhou University, Zhengzhou, Henan, China	
•	Scholarships for Outstanding Students, Third Prize,	1996,1997
	Zhengzhou University, Zhengzhou, Henan, China	
•	Outstanding Student Medal in Department of Electrical Engineering	1998
	Zhengzhou University, Zhengzhou, Henan, China	

# SELECTED PUBLICATIONS

# Journals

2010

- H.D. Cheng, Juan Shan, Wen Ju, Yanhui Guo and Ling Zhang, "Automated Breast Cancer Detection and Classification Using Ultrasound Images: A Survey", Pattern Recognition, Vol. 43, No. 1, pp. 299-317, 2010.
- H.D. Cheng, Yanhui Guo and Yingtao Zhang, "Breast Ultrasound Image Segmentation Based On Particle Swarm Optimization And The Characteristics of Breast Tissue", accepted by New Mathematics and Natural Computation, in press.

- H.D. Cheng, **Yanhui Guo** and Yingtao Zhang, "A Novel Image Segmentation Approach Based on Neutrosophic Set and Improved Fuzzy C-means Algorithm", accepted by New Mathematics and Natural Computation, in press.
- H.D. Cheng, **Yanhui Guo** and Yingtao Zhang. "A Novel Approach to Image Thresholding Based on 2D Homogeneity Histogram and Maximum Fuzzy Entropy", accepted by New Mathematics and Natural Computation, in press.

### 2009

- Yanhui. Guo and H.D. Cheng. "New neutrosophic approach to image Segmentation", Pattern Recognition. Vol. 42, No. 5, pp. 587-595, 2009.
- H.D. Cheng, Yanhui Guo and Yingtao Zhang. "A Novel Hough Transform Based on Eliminating Particle Swarm Optimization and Its Applications", Pattern Recognition, Vol. 42, No. 9, pp. 1959-1969, 2009.
- Yanhui Guo, H.D. Cheng, Jiawei Tian and Yingtao Zhang. "A Novel Approach to Speckle Reduction in Ultrasound Imaging", Ultrasound in Medicine & Biology, Vol. 35, No. 4, pp. 628-640, 2009.
- Yanhui Guo, H.D. Cheng and Yingtao Zhang. "A new neutrosophic approach to image denoising", New Mathematics and Natural Computation, Vol. 05, No. 03, pp.653-662, 2009.

#### 2008

- H.D. Cheng and Yanhui Guo. "A new neutrosophic approach to image thresholding", New Mathematics and Natural Computation, Vol. 4, No.3, pp. 291-307, 2008.
- Guoqing Du, Jiawei Tian, Yanhui Guo, Min Ren, Shuangquan Jiang and Ying Wang. "Quantitative evaluation of myocardial perfusion and regional systolic function by myocardial contrast stress echocardiography with computer-assisted technique in ischemic myocardium of rabbits", Chinese Journal of Cardiology (in Chinese), Vol. 36, No. 4, pp. 67-71, 2008.
- Jianhua Huang, Yingxing Yu, Yingtao Zhang, Xianglong Tang and Yanhui Guo. "A method for breast ultrasound image segmentation based on homogeneity histogram", Journal of Harbin Institute of Technology (in Chinese), Vol. 40, No. 7, pp. 80-84, 2008.

#### 2007

- Yanhui Guo, H.D. Cheng, Jianhua Huang, Wei Zhao and Xianglong Tang. "Contrast enhancement using texture histogram and fuzzy entropy", New Mathematics and Natural Computation, Vol. 3, No.3, pp. 349-365, 2007.
- Jiawei Tian, Litao Sun, Yanhui Guo, H.D. Cheng and Yingtao Zhang.

"Computerized-aid diagnosis of breast mass using ultrasound image", Medical Physics, Vol. 34, No.8, pp. 3158-3164, 2007.

2006

- Yanhui Guo, H.D. Cheng, Jianhua Huang, Jiawei Tian, Wei Zhao, Litao Sun and Yanxin Su. "Breast Ultrasound Images Enhancement Using Fuzzy Logic", Ultrasound in Medicine & Biology, Vol. 32, No. 2, pp.237-247, 2006.
- Wei Zhao, Jiafeng Liu, Xianglong Tang and Yanhui Guo. "A Continuous-Recognition-Oriented Handwritten Chinese Radical Recognition Research", Journal of Transportation Systems Engineering and Information Technology (in Chinese), Vol. 6, No. 1, pp. 51-54, 2006.

2005

 Yingtao Zhang, Jianhua Huang, Xianglong Tang and Yanhui Guo.
 "Enhancement of mammogram based on fuzzy logic technique", Journal of Harbin Institute of Technology (in Chinese), Vol. 37, No. 11, pp. 95-98, 2005.

2003

• Yanhui Guo, Jianhua Huang and Xianglong Tang. "Document Layout Analysis Based on Dilation Algorithm", Computer Engineering and Applications (in Chinese), Vol. 39, No. 34, pp. 223-225, 2003.

### **Conferences**

2008

- Yanhui Guo, H.D. Cheng, Jiawei Tian and Yingtao Zhang. "A Novel Approach to Speckle Reduction to Ultrasound Image", *the 11th Joint Conference on Information Science on Computer Vision, Pattern Recognition and Image Processing*, Shenzhen, China, 2008.
- Yanhui Guo, H.D. Cheng, Jiawei Tian and Yingtao Zhang. "A Novel Approach to Breast Ultrasound Image Segmentation Based on the Characteristics of Breast Tissue and Particle Swarm Optimization", *the 11th Joint Conference on Information Science on Computer Vision, Pattern Recognition and Image Processing*, Shenzhen, China, 2008.
- Yanhui Guo, H.D. Cheng, Wei Zhao and Yingtao Zhang. "A Novel Hough Transform Based on Eliminating Particle Swarm Optimization and its Applications", *the 11th Joint Conference on Information Science on Computer Vision, Pattern Recognition and Image Processing*, Shenzhen, China, 2008.
- Yanhui Guo, H.D. Cheng, Wei Zhao and Yingtao Zhang. "A New Neutrosphic Approach to Image Thresholding", *the 11th Joint Conference on Information*

Science on Computer Vision, Pattern Recognition and Image Processing, Shenzhen, China, 2008.

- Yanhui Guo, H.D. Cheng, Wei Zhao and Yingtao Zhang. "A New Neutrosophic Approach to Image Denoising", *the 11th Joint Conference on Information Science on Computer Vision, Pattern Recognition and Image Processing*, Shenzhen, China, 2008.
- Yanhui Guo, H.D. Cheng, Wei Zhao and Yingtao Zhang. "A Novel Image Segmentation Algorithm Based on Fuzzy C-means Algorithm and Neutrosophic Set", *the 11th Joint Conference on Information Science on Computer Vision, Pattern Recognition and Image Processing*, Shenzhen, China, 2008.
- Jiawei Tian, Chunping Ning, Yanhui Guo, Xianglong Tang, Ying Wang and H.D. Cheng. "Effect of a Novel Segment Algorithm on Radiologist's Diagnosis of Masses Using Breast Ultrasound Imaging", the 11th Joint Conference on Information Science on Computer Vision, Pattern Recognition and Image Processing, Shenzhen, China, 2008.

#### 2005

 Yanhui Guo, H.D. Cheng, Jiawei Tian and Wei Zhao. "Fuzzy Logic Approach to Breast Ultrasound Image Enhancement", the 8th Joint Conference on Information Science on Computer Vision, Pattern Recognition and Image Processing. Salt Lake City, Utah, USA, July. 26-30,2005.

#### 2003

• Yanhui Guo, Jianhua Huang and Xianglong Tang. "A Novel Mammogram Enhancement Algorithm Using Fuzzy Logic Technique", *the 7th Joint Conference on Information Science on Computer Vision, Pattern Recognition and Image Processing*, Cary, North Carolina, USA, 2003.