

Chapter 5

Advanced Fuzzy Methods for Mammography Image Analysis

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ABSTRACT

Breast cancer is the second most common type of cancer worldwide and one of the most common causes of cancer deaths. Worryingly, breast cancer incidence rates have increased over recent years. Computer Aided Diagnosis (CADx) systems are designed to help radiologists identify cancerous signs earlier, and hence to reduce the death rate. These systems involve at least two main stages: feature extraction to derive useful information from the images, and diagnosis which is typically handled as a machine learning/pattern classification problem. For breast cancer diagnosis, x-ray mammography is the main modality of diagnosis. The inherent fuzziness in the nature of mammography images makes fuzzy set theory a useful technique for handling these images. It is used as a well-suited tool to extract meaningful information from inexact data and generate appropriate solutions. In this chapter, the authors present a fast overview of some fuzzy-based methods for computer-aided detection and computer aided diagnosis of breast cancer using mammography images. Their focus is on fuzzy logic-based methods developed for mammogram enhancement, microcalcification (MC) detection, and detection and classification of masses.

INTRODUCTION

Breast cancer is a serious disease affecting many women and one of the most common cancers in that population. Consequently, breast cancer has become an important health concern in many

countries. For instance, in Canada an estimated 22,700 women have been diagnosed with breast cancer in 2009 (Canadian Cancer Society, 2009). However, successful diagnosis of breast cancer in its early stages can lead to a significant chance of full recovery. Although considerable improve-

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ments have been made in breast cancer detection through periodic screenings, a number of cases are still missed due to a variety of reasons.

Mammography is one of the most effective methods for early detection of breast cancers (Berman, 2007). On the other hand, mammography images are among the most difficult medical images to interpret, since the features that indicate disease are typically very small and there is a wide range of anatomical patterns that can occur. Also, visually analysing these images is a laborious, time consuming, and expensive task. Furthermore, each individual scan is prone to interpretation errors (Lee, 2007; Ries, *et al.*, 2004). Consequently, some lesions are missed or misinterpreted (Morton, *et al.*, 2006). Therefore, there is a growing interest in incorporating automated computer-based systems to analyse these images. Computer-Aided Diagnosis (CADx) usually involves at least two main stages: feature extraction to derive useful information from the images, and diagnosis which is typically handled as a machine learning/pattern classification problem. The outcomes of these systems play a key role for radiologists to diagnose breast cancer in its early stages. To this extent, over the past years, many approaches have been proposed to help in the detection of breast cancer (Cheng, *et al.*, 2006; Guliato, *et al.*, 2008; Mudigonda, *et al.*, 2000; Rangayyan, *et al.*, 2007; Sahiner, *et al.*, 2001; Tang, *et al.*, 2009).

During the last couple of decades, fuzzy set theory has been successfully applied to many fields, such as pattern recognition, control systems, and medical applications. Fuzzy set theory has also been effectively used to develop various techniques in image processing tasks including mammography images. The existence of inherent “fuzziness” in the nature of these images in terms of uncertainties associated with definition of edges, boundaries, and contrast makes fuzzy set theory an interesting tool for handling these applications. In this chapter, we provide a fast overview of some recently developed fuzzy-based systems for the analysis of mammography images.

BREAST CANCER DIAGNOSIS USING MAMMOGRAPHY AND COMPUTER-AIDED DIAGNOSIS SYSTEMS

Mammography is currently the most reliable and cost-effective way to detect early breast cancer. It can detect small lumps even before they can be felt by hand (Ng & Muttarak, 2003). Mammography is a widely accepted imaging method used for routine breast cancer screening as it uses low-dose x-rays for examination and can detect even small cancer signs. It generally captures four images with two views for each breast (Lewis, 1999). These images are reviewed by a radiologist to check for any abnormalities. However, a small number of cancers cannot be detected by mammography examination due to some reasons such as: (1) the cancer is located in a part of the breast that is difficult to screen; (2) the cancer is hidden by normal breast tissue; (3) it is growing in a way that does not change the surrounding normal breast tissue and as a result may not be well visible (Tang, *et al.*, 2009). These factors sometimes increase the false positive and/or false negative rates in cancer diagnosis. Furthermore, each individual scan is prone to interpretation error since visual analysis of radiographic images is subjective. While one expert may identify a particular lesion as a candidate, another radiologist may rate the same lesion as insignificant (Berman, 2007; Morton, *et al.*, 2006). In order to address this problem, a second opinion may be used. Double reading can be utilised to reduce the proportion of missed cancers (Brown, *et al.*, 1996; Warren & Duffy, 1995). The basic idea is to have two radiologists read the same mammograms which in turn can significantly increase the sensitivity ratio (Warren & Duffy, 1995). However, human re-interpretation is costly and the associated workload is high.

Due to the above reasons, there is a growing interest in incorporating automated techniques to analyse and diagnose these images. Computer Aided Diagnosis (CADx) systems are developed

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