

# Breast Density Segmentation Using Texture

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**Abstract.** This paper describes an algorithm to segment mammographic images into regions corresponding to different densities. The breast parenchymal segmentation uses information extracted for statistical texture based classification which is in turn incorporated in multi-vector Markov Random Fields. Such segmentation is key to developing quantitative mammographic analysis. The algorithm's performance is evaluated quantitatively and qualitatively and the results show the feasibility of segmenting different mammographic densities.

## 1 Introduction

Breast parenchymal density refers to the prevalence of fibroglandular tissue in the breast as it appears on a mammogram. Many studies have stressed the importance of breast density and it has been shown that breast density is an important factor in the development and risk of breast cancer [1]. The findings are intuitively appealing, since breast cancer mostly arises from the epithelial lining of the ductal/lobular glands. Segmentation of the mammogram into different mammographic densities is useful for risk assessment, quantitative evaluation of density changes, mammogram matching, region enhancement etc. However segmentation of the breast to even a simple fatty and non-fatty set of regions is much more difficult than it appears due to the large differences in parenchymal type appearances and the variability of image acquisition and acquisition parameters.

A small number of articles have suggested ways to segment the mammographic breast parenchyma. Miller and Astley [2] were the first to attempt to automatically identify regions in the breast corresponding to adipose and fibroglandular tissue, and they showed that texture analysis forms a good basis for automatically classifying breast tissue. For their classification, they investigated granulometry techniques (grey-level opening operations) and Laws' texture energies (filtering with a small set of masks depicting certain features such as lines and spots). However, their process failed on dense tissue that was relatively uniform. This may have been due to the low resolution of the images in the database that was used, and/or the size of the neighbourhoods used for processing. Zwiggelaar *et al.* [3] investigated the use of an Expectation-Maximisation algorithm on grey-level values and texture feature vectors (comprised of the difference in grey-level from the four closest neighbours) for mammogram segmentation. The results are shown on an undefined number of classes that can be as low as 3, - including the

pectoral muscle. Comparison of the proportion of dense tissue with an estimate provided by a radiologist looking at the image showed agreement of 67%.

All mammograms, normal or abnormal, from either young or an older woman, are textured: the texture of a region being a visual expression of its anatomical make up. Texture often remains largely invariant even to relatively large anatomical changes. This leads directly to the idea of segmenting each mammogram into texture regions for which the texture is deemed homogeneous for use in mammogram analysis. The success of the statistical based texture classification framework for breast pattern classification [4] motivated the investigation of textons and texture for a more local segmentation or classification of the breast area. This paper presents a method for segmenting a mammogram into different densities using texture based statistical modelling.

## 2 Method

The segmentation algorithm presented in this paper uses textons in a Hidden Markov Random Field (HMRF) framework to achieve breast tissue/density segmentation. Textons (texture primitives) [4], are defined as the centres of the clustered filter responses achieved via convolution with a filter bank followed by nearest neighbour matching. First, we construct a texton dictionary by processing a large number of segmented mammograms and then aggregating and clustering the filter responses using K-means analysis. Given the texton dictionary, each image pixel in the breast region is assigned a label by the texton which lies closest to it in the filter space. It is considered that pixels from similar tissue have similar texture properties as texture often remains largely invariant even to relatively large anatomical changes such as involution and use of HRT.

MRF theory provides a convenient and consistent way of modelling. Context-dependent entities such as image pixels, corresponding vectors and correlated features by characterising mutual influences among such entities using conditional MRF distributions. A MRF is a collection of random variables which are defined on a finite lattice, either regular or irregular and where each variable interacts with some subgroup of that lattice termed its neighbourhood [5]. The MRF framework used is an extension of MRFs from scalar intensity images (2-D) to vector images [6]. The algorithm includes Pseudo Likelihood for parameter estimation. We developed the extension in order to enable MRFs to be used for feature vector image segmentation, and to incorporate estimation of all the parameters. The multi-vector Gaussian Hidden Markov Random Fields (GHMRFs) based on the texton feature vectors incorporate both contextual and spatial neighbourhood information. The multi-vector image representation which is achieved using the filter bank [7] results in a segmentation which is superior to the segmentation of corresponding scalar images [8]. The tissue segmentation is achieved as the result of applying the Iterated Conditional Modes (ICM) algorithm proposed by Besag [9] followed by Expectation - Maximisation (EM) and Pseudo Likelihood evaluation for estimating the unknown needed model parameters until the resulting segmented images converge. An initialisation of probabilistic moments is incorporated into a Gaussian probability model for each