Texture Based Mammogram Classification and Segmentation

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Abstract. Several studies have showed that increased mammographic density is an important risk factor for breast cancer. Dense tissue often appears as textured regions in mammograms, so density and texture estimation are inextricably linked. It has been demonstrated that texture classes can be learned, and that subsequently textures can be classified using the joint distribution of intensity values over extremely compact neighbourhoods. Motivated by the success of texture classification, we propose an fully automated scheme for mammogram texture classification and segmentation. The classification method first has a training step to model the joint distribution for each breast density class. Subsequently, a statistical comparison is used to determine the class label for new images. Inspired by the classification, we combine the so-called image patch method with a HMRF(Hidden Markov Random Field) to achieve mammogram segmentation.

1 Introduction

Many studies have stressed the importance of breast density, which has been shown to be an important factor in breast cancer risk [Byng et al., 1996], [Saftlas and Szklo, 1987], [Oza and Boyd, 1993]. Wolfe was the first to study the relationship between breast patterns and risk. He proposed four breast density classes: N1, P1, P2 and NY, which represent respectively: normal breast tissue, fatty tissue, dense tissue and very dense tissue. N1 and P1 are considered low risk whereas P2 and NY are high risk classes. Later, the American College of Radiologists suggested a modification, known as the BI-RADS classification [American College of Radiology,1998]. BI-RADS generally follows Wolfe, and so in this paper, we use Wolfe Patterns, though it should be understood that our approach can be adapted straightforwardly to other classifications (BI-RADS, SCC). The goal of this paper is to use the image patch method to classify mammograms and to segment the breast into different regions, each representing a different tissue type – both based on the Wolfe classification. The idea of a texture is intuitively familiar. For the past 40 years, researchers have analysed textures in terms of what have been called "textons", which may be thought of as the

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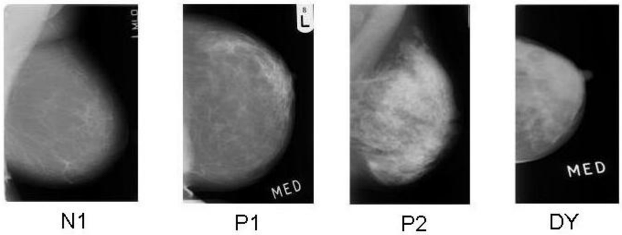

Fig. 1. Example mammograms of Wolfe Pattern

basic building blocks of a texture, i.e., a texture can be conceptualised as a suitable geometric and statistical repetition of its textons. Numerous definitions have been proposed to make precise the concept of texture and texton, and for deriving textons automatically from images. In one recent proposal, a texton was defined by Leung and Malik as a cluster centre in a suitable filter response space [Leung and Malik, 2001]. This motivated us to explore how textons could be adapted to the mammogram density evaluation.

2 Method

2.1 A Statistical Model for Breast Classification

The aim in this section is to assign a single Wolfe class to each mammogram. A set of 200 mammograms were chosen randomly from the Oxford Database, collected and digitised for the "Screen" project [Evertsz et al., 2000b], [Evertsz et al., 2000a]. The background, pectoral muscle and labels are removed using Petroudi's method [Petroudi and Brady 2001], and the mammogram pixel values are normalized to be in the range 0 to 1. 20 mammograms were then chosen randomly from each Wolfe Pattern class as the training set.

The classifier is divided into two stages: a training stage in which statistical distribution models of texture classes are learnt from training examples; and a subsequent classification stage where test images (none of the training images are subsequently used for testing) are classified by comparing their distributions to the learnt models. In the *training stage*, for each pixel of the training image, the raw pixel intensities of a $N*N$ square neighbourhood around that point are taken and row reordered to form a vector in an N^2 dimensional feature space. These "image patch" vectors are then aggregated over images from the same texture class and clustered together, and exemplars (textons) chosen via K-means clustering [Duda et al., 2001]. Finally, all the textons learnt from the (four, in this case) different classes are brought together to form a single texton dictionary. The choice of clustering each density class separately was made so that important texture primitives can be learnt from each class. In the case of mammograms, five textons are chosen from each class – greedy