A Probabilistic Approach for the Simultaneous Mammogram Registration and Abnormality Detection

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Abstract. In this paper, we present a new method for simultaneously registering mammograms and detecting abnormalities. We assume that pixels can be divided into two classes: normal tissue and abnormalities (lesions). We define the registration constraints as a mixture of two distributions which describe statistically image gray-level variations for both pixel classes. The two distributions are weighted at each pixel by the probability of abnormality presence. Using the Maximum A Posteriori, we estimate the registration transformation and the probability map of abnormality presence at the same time. We illustrate the properties of our technique with some experiments and compare it with some classical methods.

1 Introduction

Mammograms are often interpreted by comparing left and right breast images or different mammograms of a same patient. Mammogram comparisons help radiologists to identify abnormalities and determine their clinical significance [1]. In the CAD context, image comparisons are not straightforward. The registration of images must be carried out to compensate for some normal differences that can cause high false-negative rates in abnormality detection schemes [2].

Several researchers have used the subtraction of registered images as a comparative means by which to detect abnormalities [3]. The obtained asymmetry image is then thresholded to extract suspicious regions. Thus, the success of the detection task depends on the preliminary registration process.

On the other hand, the registration problem is usually expressed as a minimization of an energy composed of a regularization term and a similarity term. Usually, similarity criteria rely on some assumptions about gray-level dependencies between images [4], which are not valid in the presence of abnormalities. The registration can be improved by including in the model some knowledge about these abnormalities, as it was done in [5, 6, 7] and for the optical flow estimation in [8].

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In this paper, we present a mixture-based technique where pixels are classified into a normal tissue class and an abnormality class. The registration constraints are then defined as a mixture of two distributions describing gray-level characteristics of the two classes and which are weighted at each pixel by the probability of abnormality presence. The main feature of our model is the possibility to combine image registration and the detection of abnormalities, so as to take proper advantage of the dependence between the two processes.

The mixture-based technique and its mathematical formulation are presented in Section 2. In Section 3, we illustrate the method behavior on some examples and compare it with some classical techniques.

2 Method

Let I and J be two images defined on a discrete grid Ω_d associated to $\Omega = [0,1]^2$ and called respectively source image and target image. Image coordinates are matched using transformations ϕ which map Ω_d into itself. We assume that lesions may be present in the images. Let L be the lesion map which associates to each pixel of Ω_d its probability to belong to a lesion in I or J. Assuming that all variables are realizations of some random fields, Bayes rule can be expressed as:

$$p(\phi, L|I, J) \; = \; \frac{p(I, J|\, L, \phi)\, p(\phi)\, p(L)}{p(I, J)}.$$

For the sake of simplicity, we have assumed in the above formula that the deformation ϕ and the lesion map L are independent (i.e. $p(\phi, L) = p(\phi)p(L)$). We can estimate the pair (ϕ, L) as the solution of the Maximum A Posteriori (MAP):

$$(\widetilde{\phi}, \widetilde{L}) = \arg\max{}_{(\phi,L)} \; p(I, J|\phi, L)\; p(\phi)\; p(L)\,.$$

To ensure that the transformations remain smooth, we assume that they arise from the Gibbs distribution:

$$p(\phi) = \frac{1}{Cst} e^{-H_d(\phi)} \,, \tag{1}$$

where H_d is a discrete elasticity potential [9] (a continuous version is given by Equation (5)). We also assume that the lesion map arises from a Gibbs distribution:

$$p(L) = \frac{1}{Cst} e^{-R_d(L)} \,, \tag{2}$$

where R_d is a discrete energy of regularization. We use in this paper an energy restricting the amount of abnormal pixels in the images via a real parameter α_L:

$$R_d(L) = \alpha_L \sum_{x \in \Omega_d} L(x)\,.$$

More specific terms should be defined to describe the spatial configurations of each type of lesion. We will investigate the use of such energies in the future.