Breast lesion Segmentation in Ultra-Sound images based on super-pixels and high-level descriptors

Joan Massich[a] and Guillaume Lemaître[a,b] and Joan Martí[b] and Fabrice Mériaudeau[a]

[a]LE2I-UMR CNRS 6306, Université de Bourgogne, 12 rue de la Fonderie, 71200 Le Creusot, France;
[b]ViCOROB, Universitat de Girona, Campus Montilivi, Edifici P4, 17071 Girona, Spain

ABSTRACT

This document shows the desired format and appearance of a manuscript prepared for the Proceedings of the SPIE. It contains general formatting instructions and hints about how to use LaTeX. The LaTeX source file that produced this document, `article.tex` (Version 3.3), provides a template, used in conjunction with `spie.cls` (Version 3.3).

Keywords: Breast Ultra-Sound, Machine-Learning based Segmentation

1. INTRODUCTION

Breast cancer is the second most common cancer (1.4 million cases per year, 10.9% of diagnosed cancers) after lung cancer, followed by colorectal, stomach, prostate and liver cancers.[1] In terms of mortality, breast cancer is the fifth most common cause of cancer death. However, it place as the leading cause of cancer death among females both in western countries and in economically developing countries.[2]

Medical imaging plays an important role in breast cancer mortality reduction, contributing to its early detection through screening, diagnosis, image-guided biopsy, treatment follow-up and suchlike procedures.[3] Although Digital Mammography (DM) remains the reference imaging modality, US imaging has proven to be a successful adjunct image modality for breast cancer screening,[3,4] specially as a consequence of the discriminative capabilities that US offers for differentiating between solid lesions that are benign or malignant[5] so that the amount of unnecessary biopsies, which is estimated to be between $65 \sim 85\%$ of the prescribed biopsies,[6] can be reduced[7] in replacing them by short-term US screening follow-up.[8]

Figure ... shows ... what doctors look for.

Analysing figre ... it can be observed that most of the markers depend on the lesion delineation. Therefore in order to develop releable Computer Aided Diagnose (CAD) systems accurate segmentations to properly delineate the lesions are needed. This article presents a segmentation technique based on classifying superpixels based on their appearance.

2. SEGMENTATION METHODOLOGY DESCRIPTION

Optimization methodologies offer a standardized manner to approach segmentation by minimizing an application-driven cost function.[9] Figure 1 illustrates a generic representation of the segmentation strategy here adopted to delineate breast lesions in US images. The overall segmentation can be seen as a three steps strategy: (1) a mapping or encoding of the image into a discrete set of elements, (2) the optimization stage which is formulated as *metric labelling* problem, and (3) a remapping or recoding of the labels obtained in the previous stage to produce the final delineation.

In order to formulate the segmentation as a metric labelling problem, the image is conceived as a discrete set of elements $\mathcal{S}$ that need to be labelled using a label l from the labelling set $\mathcal{L}$ (i.e. $l \in \{\text{lesion, lesion}\}$ or $l \in \{\text{lungs, fat, parenchyma, .. ., lesion}\}$). Let $\mathcal{W}$ be all the possible labelling configurations of the set $\mathcal{S}$ given $\mathcal{L}$, and let $U(\cdot)$ be a cost function encoding how good is a labelling configuration $\omega \in \mathcal{W}$ based on the appearance of

Further author information: (Send correspondence to J.M.)
J.M.: E-mail: joan.massich@u-bourgogne.fr

the elements in $\mathcal{S}$, their relation and some designing constrains. Then, the desired segmentation $\hat{\omega}$ corresponds to the labelling configuration minimizing this cost function, $\hat{\omega} = \arg\min_{\omega} U(\omega)$.

?? shows the cost details, and **??** offers an interpretation of the terms found in **??** and fig. 1 applied to segmentation of breast tissues in US images.

$$U(\omega) = \sum_{s \in S} D_s(\omega_s) + \sum_{s} \sum_{r \in \mathcal{N}_s} V_{s,r}(\omega_s, \omega_r) \tag{1}$$

Despite the fact that $\mathcal{S}$ could be any discrete set representing the image, like pixels, overlapping or non overlapping windows, etc.; for this application, the set $\mathcal{S}$ is the super-pixels representation of the image. The super-pixels can be seen as the output of a over-segmentation process or as a set of pixel collections that are contiguous and coherent with respect to some metric. Either way super-pixels are no overlapped irregular groups of similar connected pixels.

The $U(\omega)$, as defined in **??**, is the combination of two independent cost functions that are simultaneously minimized as a whole. The former term, $D_s(\omega_s)$, is referred to as the *data* term, while the latter, $\sum_{r \in \mathcal{N}_s} V_{s,r}(\omega_s, \omega_r)$, is indistinctly referred to as the *pairwise* or *smoothing* term. The data term is the cost of assigning a particular label l (also denoted ω_s) to the site s based on the image data of s, whereas the pairwise or smoothing term represents the cost of the assignation ω_s taking into account the labels of its neighbour sites, ω_r, $r \in \mathcal{N}_s$.

As illustrates fig. 1, in order to produce a segmentation, the image is *mapped* or represented using *super-pixels*.

the elements here used

The image

Figure 1. Conceptual block representation of the segmentation methodology

3. FEATURE DESCRIPTION

Features description

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