

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

^aLE2I-UMR CNRS 6306, Université de Bourgogne, 12 rue de la Fonderie, 71200 Le Creusot, France;

^bViCOROB, 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 malignant⁵ so that the amount of unnecessary biopsies, which is estimated to be between 65 ~ 85% of the prescribed biopsies,⁶ can be reduced⁷ in replacing them by short-term US screening follow-up.⁸

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

Analysing figure ... 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 tissues or 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 \mathcal{S} , (2) the optimization stage which is formulated as *metric labelling* problem, and (3) re-mapping or re-coding of the labels obtained from the previous stage to produce the final delineation.

In order to formulate the segmentation like 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. $l \in \{\text{lesion}, \overline{\text{lesion}}\}$ or $l \in \{\text{lungs}, \text{fat}, \dots, \text{lesion}\}$). 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 the

Further author information: (Send correspondence to J.M.)

J.M.: E-mail: joan.massich@u-bourgogne.fr

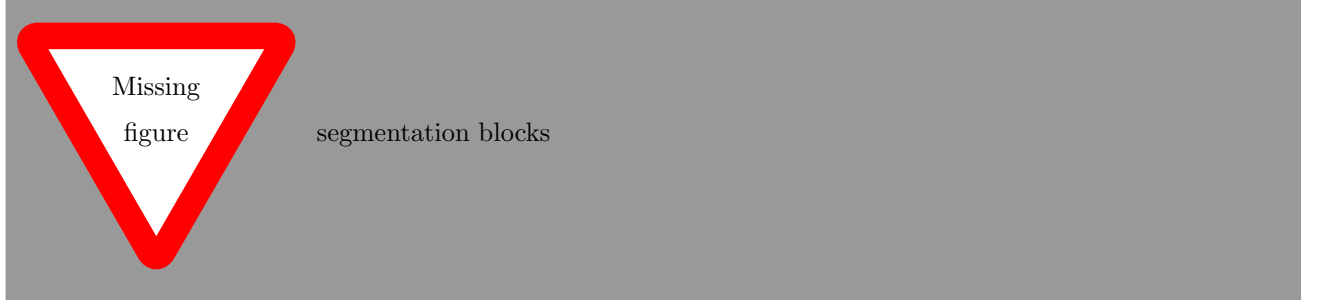


Figure 1. Conceptual block representation of the segmentation methodology

elements in \mathcal{S} , their inner relation and some designing constrains. Then, the desired segmentation $\hat{\omega}$ corresponds to the labelling configuration that minimize this cost function, as described in ??.

$$\hat{\omega} = \arg \min_{\omega} U(\omega) \quad (1)$$

Selecting the appropriated strategy to minimize the cost function $U(\omega)$ is part of the designing process since depending on the nature of $U(\cdot)$ and \mathcal{W} , not all the minimizing strategies are suitable or desirable.

?? shows the details of the cost function which combines two independent cost. Both costs are shaped by f , evaluated in \mathcal{W} and need to be 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.

$$u(\omega) = \sum_{s \in \mathcal{S}} d_s(\omega_s) + \sum_s \sum_{r \in \mathcal{N}_s} v_{s,r}(\omega_s, \omega_r) \quad (2)$$

?? takes the study case of delineating breast tissues in US images, to relate ?? and fig. 1, and offer an interpretation their terms and elements.

Despite the fact that f can be any discrete set representing the image (i.e. pixels, overlapping or non overlapping windows, etc.), for this application, f is the super-pixels representation of the image.¹⁰ ?? shows a Breast Ultra-Sound (BUS) image example and a its associated super-pixels representation \mathcal{S} coloured according to the image's Ground Truth (GT). Bear in mind, that the ultimate goal given an unseen BUS image is to represent the image as a set of super-pixels and infer the appropriated labelling for each of them.

Given a label configuration $\omega \in \mathcal{W}$, the data term penalizes the assignation of a particular label to a particular image element or site ($\omega_s = l$) based on the data associated to s . In this manner $D_s(\omega_s = l_3) \ll D_s(\omega_s = l_7)$.

Designing and defining out of the box an obscure heuristic for $D(\cdot)$ that accomplish the desired behaviour, is rather complicated. However Machine Learning (ML) offers a clean an easy manner of generating image or data models based on training samples

the $u(\omega)$ is the combination of two independent cost functions both determined by f , that need to be simultaneously minimized as a whole.

despite the fact that f could be any discrete set representing the image, like pixels, overlapping or non overlapping windows, etc.; for this application, the set f 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.¹⁰

In ??, 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 image element (or site) s based on its associated image data. To illustrate how the sites contribute to the data term, ?? illustrates the cost of labl

, 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

3. FEATURE DESCRIPTION

Features description

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