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

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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 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 $l \in \{\text{lungs}, \text{fat}, \cdots, \text{lesion}\}$). 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

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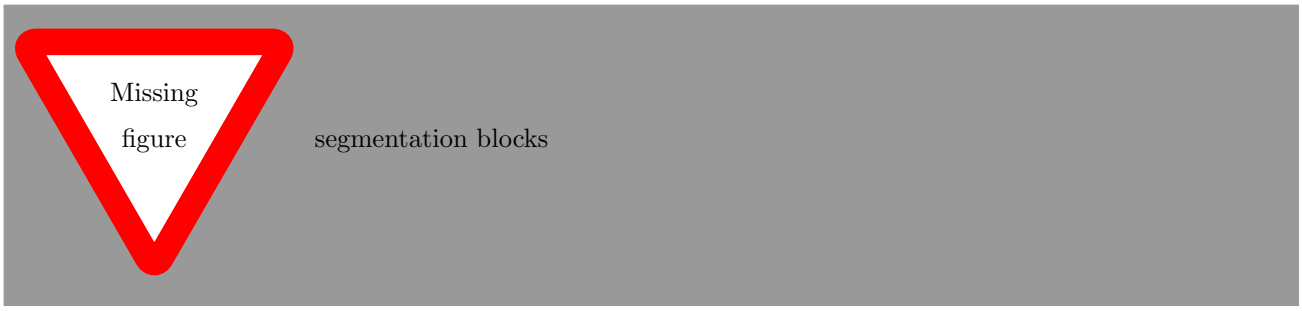

Figure 1. Conceptual block representation of the segmentation methodology

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 **??**.

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

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 $\int$, 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.

$$U(\omega) = \sum_{s\in s} D_s(\omega_s) + \sum_{s} \sum_{r\in\mathcal{N}_s} V_{s,r}(\omega_s, \omega_r) \tag{2}$$

?? 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 $\int$ can be any discrete set representing the image (i.e. pixels, overlapping or non overlapping windows, etc.), for this application, $\int$ 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.

2.1 Data term

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 $D_s(\omega_s = l_3) << D_s(\omega_s = l_7)$. To perceive the effect or behaviour of this data term, **??** shows some labelling configurations $\omega^{'}$ where all the sites share the same label, $\omega' \in \{\omega_s = l,\ \forall s \in \mathcal{S}\}$

Designing $D(\cdot)$ that accomplish the desired behaviour by defining an obscure heuristic, is rather complicated. Therefore, an easier and cleaner approach is to take advantage of Machine Learning (ML) techniques. The idea is to generate image or data model for each class, based on training samples, and let $D(\cdot)$ be a distance or goodness measure reflecting how likely is for the site s to belong to class l. Figure 1 shows how this is incorporated to the segmentation framework here proposed. Each site s is treated as a sample and the features to describe the site are extracted from the original image. For the work here reported, a Support Vector Machine (SVM) classifier is used to determine the data model during the training stage and during testing stage $D_s(\omega_s = l)$ corresponds to the distance between the testing sample and the vector supporting the data model associated to l.

Notice that defining $D(\cdot)$ in this manner allows for many designing choices such as: which features to use, how is the class model created: which classifier, which training policy; or, how is defined the relation between the testing sample and the model. Further discussion regarding the feature choices can be found in **??**, whereas other designing choices regarding ML are out of the scope for this work.

2.2 Pairwise or smoothing term

The pairwise 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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REFERENCES

1. J. Ferlay, H.-R. Shin, F. Bray, D. Forman, C. Mathers, and D. M. Parkin, "Estimates of worldwide burden of cancer in 2008: GLOBOCAN 2008," *International Journal of Cancer* **127**(12), pp. 2893–2917, 2010.
2. A. Jemal, F. Bray, M. M. Center, J. Ferlay, E. Ward, and D. Forman, "Global cancer statistics," *CA: A Cancer Journal for Clinicians* **61**(2), pp. 69–90, 2011.
3. R. A. Smith, D. Saslow, K. A. Sawyer, W. Burke, M. E. Costanza, W. Evans, R. S. Foster, E. Hendrick, H. J. Eyre, and S. Sener, "American cancer society guidelines for breast cancer screening: update 2003," *CA: a cancer journal for clinicians* **53**(3), pp. 141–169, 2003.
4. W. A. Berg, L. Gutierrez, M. S. NessAiver, W. B. Carter, M. Bhargavan, R. S. Lewis, and O. B. Ioffe, "Diagnostic accuracy of mammography, clinical examination, US, and MR imaging in preoperative assessment of breast cancer," *Radiology* **233**(3), pp. 830–849, 2004.
5. A. T. Stavros, D. Thickman, C. L. Rapp, M. A. Dennis, S. H. Parker, and G. A. Sisney, "Solid breast nodules: Use of sonography to distinguish between benign and malignant lesions," *Radiology* **196**(1), pp. 123–34, 1995.
6. Y. Yuan, M. L. Giger, H. Li, N. Bhooshan, and C. A. Sennett, "Multimodality computer-aided breast cancer diagnosis with ffdm and dce-mri.," *Academic radiology* **17**(9), p. 1158, 2010.
7. S. Ciatto, M. Rosselli del Turco, S. Catarzi, D. Morrone, *et al.*, "The contribution of ultrasonography to the differential diagnosis of breast cancer.," *Neoplasma* **41**(6), p. 341, 1994.
8. P. B. Gordon and S. L. Goldenberg, "Malignant breast masses detected only by ultrasound. A retrospective review," *Cancer* **76**(4), pp. 626–630, 1995.
9. D. Cremers, M. Rousson, and R. Deriche, "A review of statistical approaches to level set segmentation: integrating color, texture, motion and shape," *International journal of computer vision* **72**(2), pp. 195–215, 2007.
10. R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk, "SLIC superpixels compared to state-of-the-art superpixel methods," 2012.