Breast Ultra-Sound image segmentation: an optimization approach based on super-pixels and high-level descriptors

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ABSTRACT

Breast cancer is the second most common cancer and the leading cause of cancer death among women. Medical imaging has become an indispensable tool for its diagnosis and follow up. During the last decade, the medical community has promoted to incorporate Ultra-Sound (US) screening as part of the standard routine. The main reason for using US imaging is its capability to differentiate benign from malignant masses, when compared to other imaging techniques. The increasing usage of US imaging encourages the development of Computer Aided Diagnosis (CAD) systems applied to Breast Ultra-Sound (BUS) images. However accurate delineations of the lesions and structures of the breast are essential to CAD systems in order to extract information needed to perform diagnosis.

This article proposes a highly modular and flexible framework for segmenting lesions and tissues present in BUS images. The proposal takes advantage of optimization strategies using super-pixels and high-level descriptors, which are analogous to the visual cues used by radiologists. Qualitative and quantitative results are provided stating a performance within the range of the state-of-the-art.

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 is ranked as the leading cause of cancer death among females in both western countries and economically developing countries.[2]

Medical imaging plays an important role in breast cancer mortality reduction, contributing to its early detection through screening for diagnosis, image-guided biopsy, treatment follow-up and suchlike procedures.[3] Although Digital Mammography (DM) remains the reference imaging modality for breast cancer screening, Ultra-Sound (US) imaging has proven to be a successful adjunct image modality.[3,4] The main advantage of US imaging, opposed to other image modalities, lies on the discriminative power US offers for visually differentiate benign from malignant solid lesions.[5] In this manner, US screening contributes to reduce the amount of unnecessary biopsies,[6] which is estimated to be between $65 \sim 85\%$ of the prescribed biopsies,[7] in favour of a less traumatic short-term screening follow-up using Breast Ultra-Sound (BUS)[8] For all these reasons, there is a growing interest in the medical community to incorporate US screening as part of the standard procedure,[9] which encourages the development of Computer Aided Diagnosis (CAD) systems using US to be applied to breast cancer diagnosis.

The American College of Radiology (ACR), in order to provide a common ground for radiologists when assessing BUS images, compiled and proposed the Breast Imaging-Reporting and Data System (BI-RADS) lexicon for BUS images.[9] A lexicon is a standardized set of markers to describe the visual cues found in BUS images that are recommended to be analysed when performing image based diagnosis. This lexicon, proposed by the ACR, can be found in this document at section 2.1.1, where visual cues of BUS images and breast structures are discussed to define feature descriptors. While visual cues are discussed further in this document, it is worth to mention here that the US BI-RADS lexicon is designed to be used by expert radiologists to characterize the

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lesions and produce a diagnosis based on the lexicon description of the lesions. This implies that radiologists, during the visual assessment of the images, locate the lesions and determine their extension prior to utilize the lexicon. Obviously, this is an intrinsic the process carried out by the trained radiologists when visually reading the images and there is no need for explicit delineation of the lesions. However, developing accurate segmentation methodologies breast lesions and structures is crucial for developing CAD systems that can take advantage of the already existing tools for characterizing the lesions.

This article proposes a highly modular and flexible framework for segmenting lesions and tissues present in BUS images. The proposal takes advantage of an energy-based strategy to perform segmentations based on discrete optimizations using super-pixels and a set of novel features analogous to the elements encoded by the US BI-RADS lexicon.[9]

2. DESCRIPTION OF THE SEGMENTATION METHODOLOGY

Optimization methodologies offer a standardized manner to approach segmentation by minimizing an application-driven cost function.[10] 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 of the image into a discrete set of elements $\mathcal{S}$, (2) the optimization stage which is formulated as a *metric labelling* problem, and (3) a re-mapping the labels obtained from the previous stage to produce the final delineation.

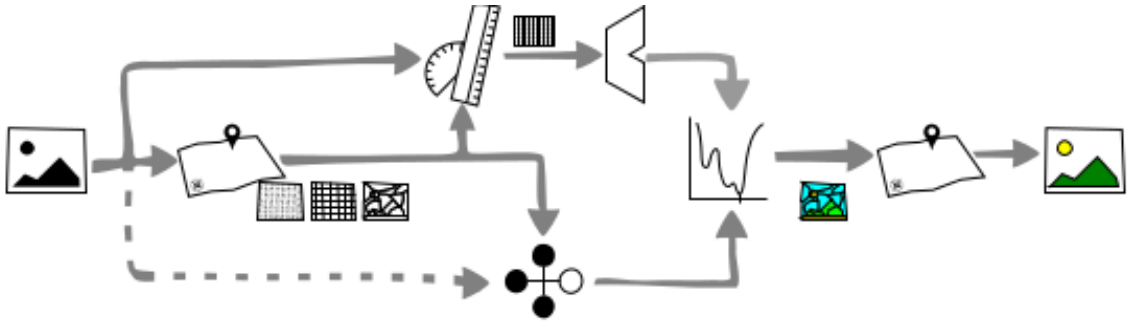


Figure 1: Conceptual block representation of the segmentation methodology

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. $\mathcal{L} \in \{\text{lesion}, \overline{\text{lesion}}\}$ or $\mathcal{L} \in \{\text{lungs}, \text{fat}, \cdots, \text{lesion}\}$). Let $\mathcal{W}$ be all the possible labelling configurations of the set $\mathcal{S}$, given $\mathcal{L}$. Let $U(\cdot)$ be a cost function encoding the goodness of the labelling configuration $\omega \in \mathcal{W}$ based on the appearance of the elements in $\mathcal{S}$, their inner relation and some designing constraints. Then, the desired segmentation $\hat{\omega}$ corresponds to the labelling configuration that minimize this cost function, as described in Equation (1).

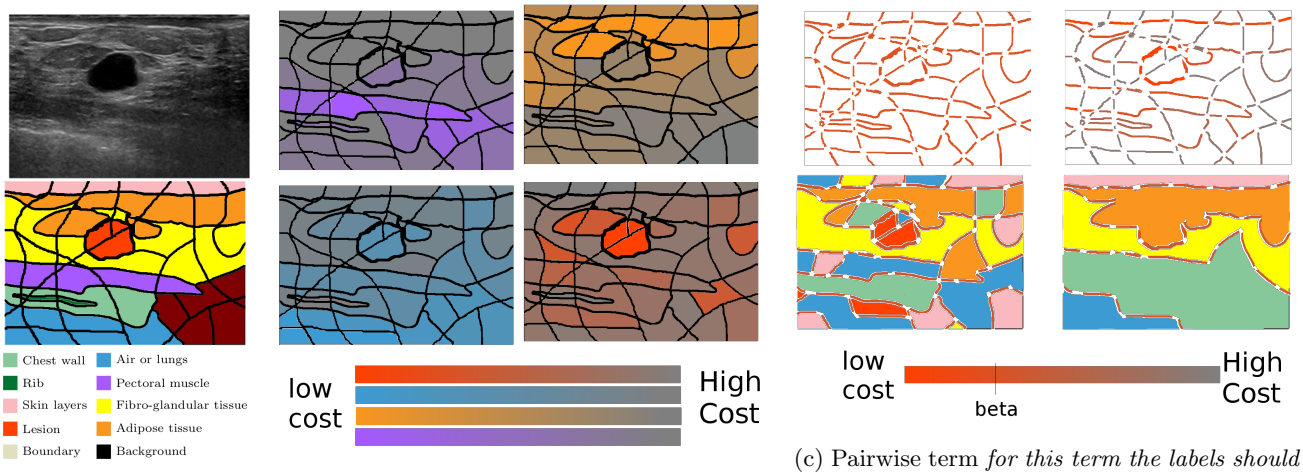
$$\hat{\omega} = \arg\min_{\omega} U(\omega) \tag{1}$$

It is worth to mention here that not all the minimization strategies are applicable or adequate to find $\hat{\omega}$. The convenience of a particular minimization strategy is determined by the nature of $u(\cdot)$ and $\sqsupseteq$ (see section 2.3).

This goodness measure $U(\cdot)$ must be defined to take into account the appearance of the target region, its relation with other regions and other designing constraints. Equation (2) describes this cost function as the combination of two independent costs that need to be simultaneously minimized as a whole.

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

The left hand side of the expression integrates the so-called *data* term, while the right hand side integrates the *pairwise* term, which is also referred as the *smoothing* term. Both terms are shaped by $\mathcal{S}$ and evaluated in



(a) Problem definition (b) Data term (c) Pairwise term *for this term the labels should be patterns and the cost be the only colour*

Figure 2: Methodology terms interpretation

the labelling space $\mathcal{W}$. Figure 2 uses the problem of delineating the tissues present in a BUS image to represent the working principles of the data and pairwise terms in eq. (2).

In general, $\mathcal{S}$ can be any discrete set representing the image (i.e. pixels, overlapping or non overlapping windows, etc.). For this work $\mathcal{S}$ is chosen to be a super-pixels representation of the image. 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.[11] Figure 2a illustrates the super-pixels idea showing a BUS image example and a its associated super-pixels representation $\mathcal{S}$ coloured according to the image's Ground Truth (GT). For the rest of this work, $\mathcal{S}$ is considered to be the super-pixels resulting from over-segmentation of the image using Quick-shift.[12]

Bear in mind that given an unseen BUS image, the ultimate goal is to represent the image as a set of super-pixels and infer the appropriated labelling for each of them. This goal requires to define: a data term, a pairwise term, and a proper minimization methodology.

2.1 The data term

Given a label configuration $\omega \in \mathcal{W}$, the data term penalizes the labelling of a particular image element or site ($\omega_s = l$) based on the data associated to s. In this manner, $D_s(\omega_s = l_{\checkmark}) << D_s(\omega_s = l_{\times})$. Figure 2b illustrates the data cost associated to some arbitrary labelling configurations to clarify the desired effect (or behaviour) of this data term (fig. 2a shows the GT of each site s). Notice that the labelling configurations ω used in fig. 2b have the particularity that all sites share the same label, $\omega \in \{\omega_s = l,\ \forall s \in \mathcal{S}\}$.

Designing an obscure heuristic to comply with the desired behaviour of $D(\cdot)$ out of the box, is rather a complicated task. Therefore, an easier and cleaner approach is to take advantage of Machine Learning (ML) techniques to design this data cost in a systematic manner based on a training stage. The idea is to generate a data model for each label (or class) in $\mathcal{L}$ from training samples, and let $D(\cdot)$ be a distance or goodness measure reflecting the likelihood for s to belong to class l. Using ML to define $D(\cdot)$ in this manners offers a systematic approach towards its design while remaining highly flexible since it allows for customizing the features to represent the data, allows for customizing the construction of the model where several classifiers and training techniques can be applied; or even to include some arbitrary constrains.

Despite details regarding the construction $D(\cdot)$ are out of the scope of this report, the rest of this section 2.1 summarizes this process. For further details the reader is referred to Massich et al.[12] The usage of ML as part of the proposed framework to determine $D(\cdot)$ is represented at the upper side of the diagram in fig. 1, which can be divided into two blocks: (a) the features to represent the samples, and (b) the tools to encode $D(\cdot)$ based on the features and the training.

2.1.1 BUS features to build the data term

Figure 3 is a three-parts illustration to graphically summarize the visual cues that can be found in BUS images. Figure 3a shows the structures present in the breast and how these are imaginary rendered using a hand-held 2D US probe. Figure 3b illustrates the lexicon proposed by the ACR.[9] *And section 2.1.1, illustrates which visual cue exploided by the lexion was targeted by the data term features proposed in Massich et al.*[12] Notice that not all the visual cues used 'composing' the lexicon are suitable to build the data term. Mass shape, orientation and margin cues do not characterize individual super-pixels but a group of contiguous super-pixels sharing the same label. Characterising supper pixels in those terms imply that super-pixels should be image elements of the same order as the lesions. This is not the case, since the bottom-line is to aggregate small regions to form the segmentation. The lesion boundary cue falls at the other extreme. To encode this visual cue as data term feature implies to use smaller super-pixels in order to be fully contained within the halo, limiting the discriminatory power of other features that need larger regions to build higher-level descriptors.

Massich et al.[12] reported that the features in section 2.1.1 extracted to describe the sample s correspond to the following:

Appearance Based on the multi-labelled GT, a Median Absolute Deviation (MAD) histogram model for every tissue label is build. The Appearance feature is computed as the Quadratic-Chi (QC) distance between histogram of s and the models.

Atlas Based on the multi-labelled GT an atlas is build to encode the label likelihood based on the location of s.

Brightness Takes an intensity descriptor of s (*i.e:* mean, median, mode) and compares it with some intensity markers of the set $\mathcal{S}$ such as the minimum intensity value, the maximum, its mean, etc.

Self-Invariant Feature Transform (SIFT)-Back-of-Features (BoF) s is represented as the occurrences of a SIFT dictionary of 36 words.[13]

Massich et al.[12] also reports that in order to incorporate multi-resolution, each super-pixel is group with its adjacent super-pixels such that $s' = \{s \cup \mathcal{N}_s\}$, the features are recalculated using s' and concatenated to the original feature descriptor. This operation can be repeated several times.

In this manner the B.Echo-texture, is mainly encoded by the SIFT-BoF but also through the Appearance feature since elements would have the same model. Acoustic Posterior is mainly captured by the Brightness feature, but the Atlas also brings in crucial information to compensate for intensity inhomogeneities caused signal attenuation present in the more posterior parts of the image. The Echo Pattern cue, encodes the echoginity of a region with respect to the adipose tissue. This can be found at the anterior part of the image and its echoginity is close to the middle of the spectrum. Appearance, Brightness and the Atlas account for such information.

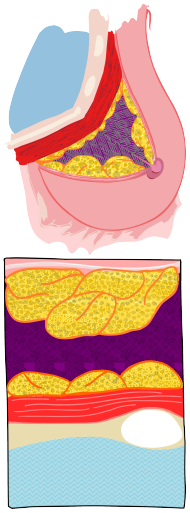
2.1.2 The data term construction

For the work here reported, a Support Vector Machine (SVM) classifier is used to determine the data model during the training stage. During testing stage $D_s(\omega_s = l)$ corresponds to the distance between the testing sample and the model associated to l as the SVM classification reward.

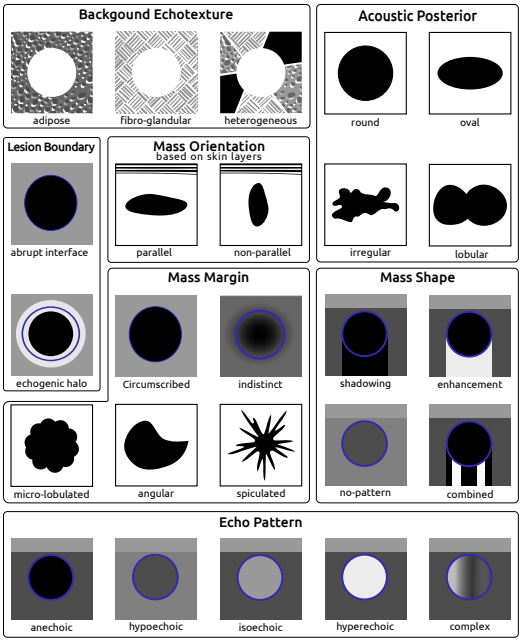
2.2 The pairwise (or smoothing) term

The pairwise term represents the cost associated to ω_s taking into account the labels of its neighbour sites, ω_r, $r \in \mathcal{N}_s$. This term models a Markov Random Fields (MRFs) or a Conditional Random Fields (CRFs). The typical form of this term, given in eq. (3), is called homogenization which acts as a regularization factor favouring configurations that have coherent labelling.

$$V_{s,r}(\omega_s, \omega_r) = \begin{cases} \beta, & \text{if } \omega_s \neq \omega_r \\ 0, & \text{otherwise} \end{cases} \tag{3}$$



(a) Breast structure



(b) Breast lesion characteristics in US screening influencing clinical management[14]

	Background	Echo-Texture	Posterior	L.Boundary	M.Orient.	M.Margin	M.Shape	E.Pattern
Appearance		x						x
Atlas			x					x
Brightness			x					x
SIFT-BoF		x						

Figure 3: Visual reference of breast structures and visual cues used for standard BUS image assessment and diagnosis.

Figure 2c offers a visual interpretation of this cost. The more fragmented is the segmentation ω, the higher the overall pairwise term would it be since every boundary brings a penalization β to the total cost $U(\omega)$. In this manner the regularization term can be seen as a post-processing or denoising stage since some sites will flip their labelling if the cost of fragmenting the regions is larger than the cost of adopting the neighbour's label.

More sophisticated smoothing terms where boundaries have different penalization based not only on site relations in $\mathcal{S}$ but also based on image information as illustrated in fig. 2c are also naturally handled by the proposed framework.[12]

2.3 Searching the best labelling configuration

Once defined $U(\omega)$ so that the cost for a particular labelling configuration ω can be computed, the problem of finding $\hat{\omega}$ corresponding to the global minimum of the space $\mathcal{W}$ of all possible labelling configurations needs to be faced.

This problem falls into the category of **NP-hard** problems. More over, due to limitations in building $U(\cdot)$ such as noise, training policies, etc. there are no guarantees that the global minimum $\hat{\omega}$ corresponds to the true labelling.

Nevertheless, there is a large body of literature proposing methodologies to find suboptimal solutions to the problem trading-off between time of convergence and accuracy of the solution reached. Szeliski et al.[15] conducted an exhaustive review in terms of solution quality and runtime of the most common energy minimization algorithms used in Computer Vision (CV), such as Iterated Conditional Modes (ICM), Simulate Anealing (SA) or Graph-Cuts (GC).

The minimization strategy used for this work is GC. This technique was initially introduced to solve CV applications by Boykov et al.[16] Soon after its introduction, it becomes the minimization technique of choice for CV problems. Since, when GC is applicable, it allows to rapidly find a strong local minima guaranteeing that no other minimum with lower energies can be found.[17] GC is applicable if, and only if, the pairwise term favours coherent labelling configurations and penalizes labelling configurations where neighbours labels differs; such is our case, given eq. (3).

3. RESULTS

A lack of public data to perform fair comparison between methodologies using a common benchmark is a recurrent problem in medical imaging. BUS imaging is no exception.[18] Therefore our framework can only be compared for the lesions segmentation case, and only against the results reported in the bibliography.

Figure 4 compares our segmentation strategy against the state-of-the-art methodologies assuming the following limitations: (a) the other methodologies' performance has been collected from the literature. (b) Since all the segmentation results are reported using different metrics, those have been translated to Area Overlap (AOV) as a common evaluation metric. (c) Evaluation datasets not only differ in image acquisition but also their sizes suffer a large variation.

Each radius (a .. p) represents a methodology from the literature. Those methodologies have been grouped in terms of ML, Active Contour Model (ACM), other methodologies, and combinations of those three classes. The figure reports the size of the dataset the authors have used for evaluation and also the AOV reported. Highlighted in blue there is also represented an experiment conduced by Pons et al.[19] where 50 BUS images with a single lesion were all delineated by 5 experts in order to study inter- and intra-observer variability of GT annotation. The experiment reported an AOV rate between 0.8 and 0.852 for the 5 actors, when counting the original GT accompanying the images.

Our segmentation results are represented as a black circle showing that those are within the state-of-the-art. A more meticulous analysis of the results is present in the complete version of the manuscript.

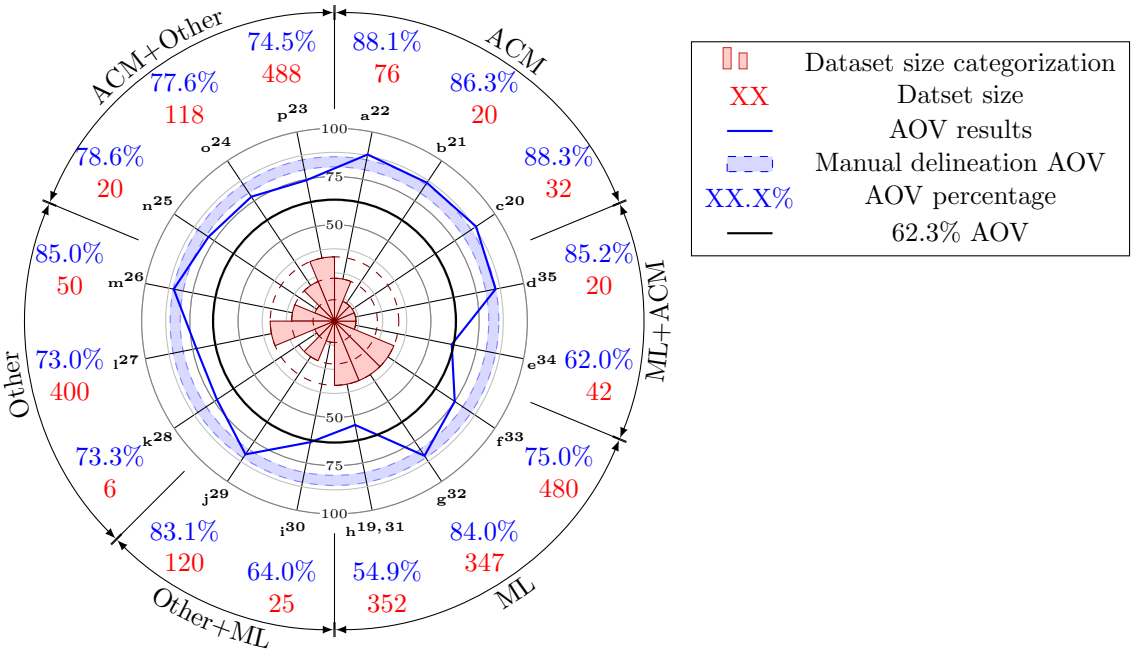


Figure 4: Quantitative AOV results

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