SIFT texture description for understanding breast ultrasound images

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Abstract. Ultra-Sound (US) imaging is the most common adjunct image modality to assess breast cancer. In order to interpret such images, texture interpretation is of major importance. This paper proposes to use Self-Invariant Feature Transform (SIFT) descriptor as texture and provides a feasible interpretation of its behavior related to the underlying depicted tissue type. The proposal has been evaluated using a set of breast images with accompanying expert-provided Ground Truth (GT) which describes all the tissues present within the images.

Key words: breast cancer, ultrasound, texture, SIFT

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. In terms of mortality, breast cancer is the fifth most common cause of cancer death. However, it places as the leading cause of cancer death among females both in western countries and in economically developing countries [3].

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 [5]. Despite Digital Mammography (DM) still remains as the image modality of reference for diagnose purposes, US offers useful complementary diagnose information due to its capabilities for differentiating between solid lesions that are benign or malignant [6]. It is estimated that between $65 \sim 85\%$ of the biopsies prescribed using only mammography imaging could be avoided if US information had been taken into account while issuing the diagnose [7].

In US images, texture is a major characteristic to distinguish between different breast tissues, which also allows assessing of the lesion's pathology [6]. Therefore, the importance of incorporating texture data from US images into Computer Aided Diagnosis (CAD) systems. A comprehensive list of texture descriptors used for detection, segmentation or diagnose tasks applied to US breast images is given in Cheng *et al.* [1]. Where most of the descriptors are ad-hock descriptors or based on well-known texture descriptors such as co-occurrence matrices, wavelet coefficients or Gray-Level Difference Method (GLDM).

In this article we propose to use SIFT descriptors in order to encode the US characteristic texture produced by the speckle noise present within the images, we evaluate its performance in annotated dataset.

2 Material and methods

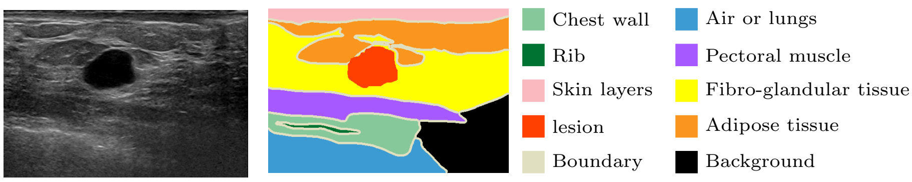
In order to evaluate the texture description of the observable breast tissues when using US screening, a set of 16 US images was acquired at the *Anonymous Hospital*. Each image corresponds to a different patient, and has accompanying multi-label GT provided by expert radiologists. Figure 1 illustrates a breast image from the dataset with its associated GT.

3 Using SIFT in order to describe different tissues present in breast US images

Self-Invariant Feature Transform (SIFT) [4] transforms key-points into scale and rotation invariant coordinates relative to local features in order to sample the magnitude and orientation of the gradients surrounding the key-point for generating a 128 element feature. In order to generate a texture descriptor out of SIFT descriptors, a regular grid is used to generate evenly sparse SIFT descriptors. At the finest resolution every single pixel of an image can be used as a key-point to extract a SIFT descriptor out of every possible position.

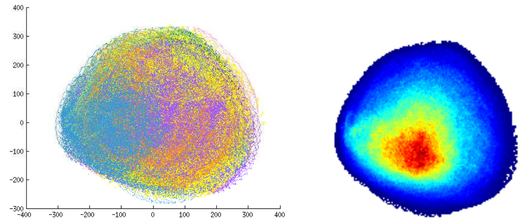
The usage of SIFT descriptor brings invariability to scale, rotation and minor affine transformations along with robustness to illumination changes [4], which allows to differentiate the tissues despite the variability from US adquisition.

The resulting space from using all the pixels as a key-point is described in figures 2, 3 and 4. For displaying purposes and easier manipulation, these figures show the two dimensional representation of the SIFT hyperspace obtained by projecting the 128 dimensions of the SIFT descriptors into a two dimensional space using Principal Component Analysis (PCA). Figure 2a shows this projection of the SIFT space into a two dimensional space. In figure 2b the projected space is discretized and an occurrence study is displayed showing the distribution of the SIFT descriptors present within the images. Figure 3 shows the occurrence study for every class, where every different tissue type is represent by different SIFT descriptors. Figure 4 qualitatively assess the description of an US image using SIFT. In fig. 4a the projected map has been arbitrarily colored, in such a manner that close projected SIFT descriptors share a similar color. This coloring associated to each SIFT descriptor is further used to remap the SIFT descriptors extracted from the original image (see fig. 4b,c).



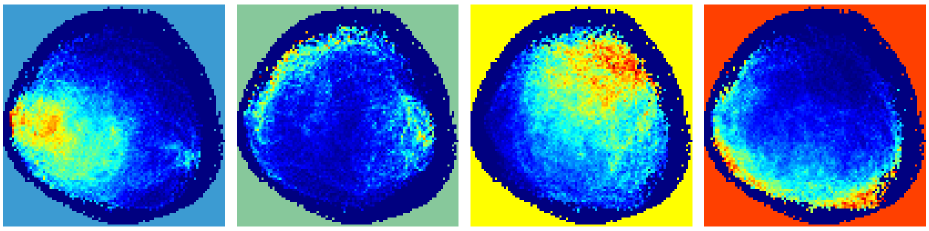
(a) (b)

Fig. 1: Dataset sample. (a) Original US image. (b) Associated GT.



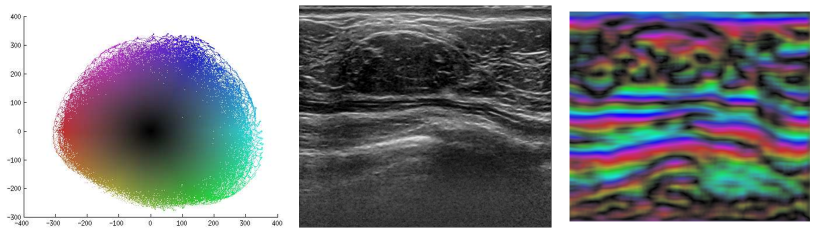
(a) (b)

Fig. 2: 2D visualization of the SIFT hyper space. (a) Projected space colored according to GT tissue labeling. (b) Occurrence density.



(a) Air or lungs (b) Chest wall (c) Fibro-glandular (d) Lesion

Fig. 3: Distribution of the SIFT descriptors for some of the tissue type.



(a) (b) (c)

Fig. 4: Low level SIFT descriptor example. (a) Arbitrary coloring of the projected SIFT space. (b) Original image. (c) Recoding of the extracted SIFT descriptors using the color coding in (a).

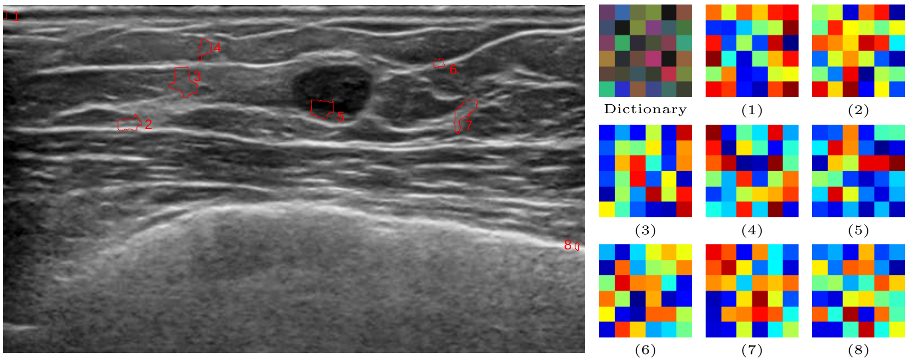


Fig. 5: SIFT-BoF descriptors qualitative analysis. (Left) image example. (Right) Dictionary representation colored using the location of the keypoint location in fig. 2a space. (1-8) Occurrence of the dictionary's key-points associated to each region highlighted in the original image.

Texture is an area property related to spatial repetition of structures, similar statistical properties of the area or both. A technique to embed statistical properties of a low level descriptor is Bag-of-Features (BoF) which analyses the occurrence of a set of keywords (or key-points) within a particular region [2].

In this proposal, the words or features representing the images are SIFT descriptors. In order to generate the dictionary that generates the BoF descriptor, the space of SIFT descriptors is clustered in order to produce a hard quantification of this space. In this case, a k-means procedure with $k = 36$ is used to generate the dictionary. To generate the BoF-SIFT feature, all the SIFT descriptors are substituted for the closest SIFT descriptor in the dictionary. Finally the texture description from a particular area is expressed as the keywords' occurrence in this area. The descriptor is normalized so that the sum of all the occurrences is 1. Figure 5 illustrates the BoF-SIFT feature for some example areas.

4 Quantitative experiment

In order to assess the usage of SIFT texture, the images are divided into superpixels, features are extracted to describe the superpixels and supervised Machine Learning (ML) procedure using Support Vector Machine (SVM) is used to infer the labeling of the superpixel. Incorporating BoF of SIFT descriptors in order to describe the superpixels improve the results of the labeling process for our preliminary experiments, however a more thorough study will be included in the final version of the document.

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