

Multi-Grid Phase Field Skin Tumor Segmentation in 3D Ultrasound Images

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Abstract- The aim of this paper is to present a new method for skin tumor segmentation in 3D ultrasound images. We consider a variational formulation the energy of which combines a diffuse interface phase field model (regularization term) and a loglikelihood computed using non parametric estimates (data attachment term). We propose a multi-grid implementation with exact solutions that has the advantage to avoid space discretization and numerical instabilities. The resulting algorithm is simple and is easy to implement in multi-dimensions. Concerning applications, we focus on skin tumor segmentation. The clinical dataset used or experiments is composed of 12 images with ground truth given by a dermatologist. Comparisons with reference methods show that the proposed method is more robust to the choice of the volume initialization. Moreover, thanks to the flexibility introduced by the diffuse interface, the sensitivity increases by 12% if the initialization is inside the lesion, and the Dice index increases by 59%, if the initialization covers the entire lesion. These results show that this new method is well-designed to tackle the problem of underestimation of tumor volumes.

Key words- 3D ultrasound images, tumor segmentation, phase field model, non-parametric estimation, multi-grid algorithm, exact solutions

I. INTRODUCTION

Ultrasound imaging is widely used in medical diagnostic because it is non-invasive and low cost. However, it is well known that ultrasound images suffer from two major defects, the low contrast and the presence of speckle noise making processing more difficult. This explains why many works are still devoted to improve ultrasound image segmentation algorithms. In this paper, we focus on the problem of skin tumor segmentation in 3D ultrasound images.

Ultrasounds have the advantage to probe at depths of 3mm or more while other non-invasive modalities, such as optical coherence tomography and reflectance confocal microscopy, are limited to a depth of 500 μm , which is insufficient to scan the bottom of deep lesions. Many works on this subject emphasize approaches based on level set methods. These latter are well adapted to deal with the variability of lesion shapes and to remove structures due to speckle patterns. However, level set segmentations tend to underestimate the size of tumors and lack accuracy at the boundary of lesions.

The frequency of the sound waves used in medical ultrasound is in the range of millions of cycles per second (megahertz, MHz). In contrast, the upper range of audible frequencies for human is around 20 thousand cycles per second (20 kHz). An ultrasound transducer sends an

ultrasound pulse into tissue and then receives echoes back. The echoes contain spatial and contrast information. The concept is analogous to sonar used in nautical applications, but the technique in medical ultrasound is more sophisticated, gathering enough data to form a rapidly moving two-dimensional grayscale image. Skin cancer is the most frequent cancer in the white population worldwide. Incidence of basal cell carcinoma (BCC), squamous cell carcinoma (SCC) and malignant melanoma (MM) is still increasing.

This trend can be counteracted by means of primary and secondary prevention because the main risk factor for skin cancer – UV-radiation – is known, and, early detected, skin cancer can be cured successfully. For early detection of skin cancer suitable risk (group) markers have to be used to identify persons at risk. In order to increase the sensitivity and specificity of early detection efforts (screening programs) new molecular markers or biomarkers should be used in the future in the field of molecular epidemiology. In this review the skin cancer problem is summarized and the possible use of new biomarkers for skin cancer development, progression, metastasis and prognosis is discussed.

The review focuses on results of gene expression profiling using array techniques and the new possibilities for the use of epigenetic biomarkers. Skin cancer is a growing problem, with currently between 2 and 3 million non-melanoma skin cancers and 132,000 melanoma skin cancers occurring each year globally. In fact, one in three

cancers diagnosed is skin cancer. The good news is that 95% of skin cancers can be successfully treated if caught at an early stage. As healthcare systems are adopting more innovative technology, there is increasing evidence that mobile health apps can help to save lives. Skin Vision empowers individuals to take their skin health into their own hands by transforming their smartphone into a medical device for skin cancer risk assessment. So far, Skin Vision has assisted in the finding of more than 35,000 skin cancer cases globally and managed to direct those people to a healthcare professional for further examination.

The service has the potential to triage those in need of treatment and could help to decrease both the average cost of treatment and the number of unnecessary doctor visits. The company has built up a customer portfolio of 1,200,000 users globally and database of 3.5 million pictures of suspicious and benign skin spots

II. THE PROPOSED SEGMENTATION METHOD

1. Llch-Exact Segmentation

This method is based on diffuse interface phase field .This latter aims at describing a process of phase separation , by which the two components of a binary fluid spontaneously separate and form domains pure in each components. Some of the steps are variational formulation , multigrid implementation with exact solution.

Evaluation is based four measures they are Dice index, sensitivity , precision, Mean absolute Distance. Dice Index is an indicator of the accuracy of a segmented volume with respect to reference volume. Dice index can be expressed as the harmonic mean of sensitivity and precision. Mean absolute distance allows to determine if the boundary of the segmented volume fits well with the boundary of reference volume. We consider 50 values of intensity between 0 and maximum and remove get area(black area above the epidermis)before the tumor segmentation is performed.

The segmentation process is stopped when the volume change between two steps is less than 0.001% of the segmented volume .Using this method yields best dice index, mean absolute distance and sensitivity and good precision which helps to tackle the problem of underestimation of tumor volume .its robust as volume inside the tumor to volume covering changes and parameters being unchanged. We get slice of initial volume for tumor from initialization covering the tumor.

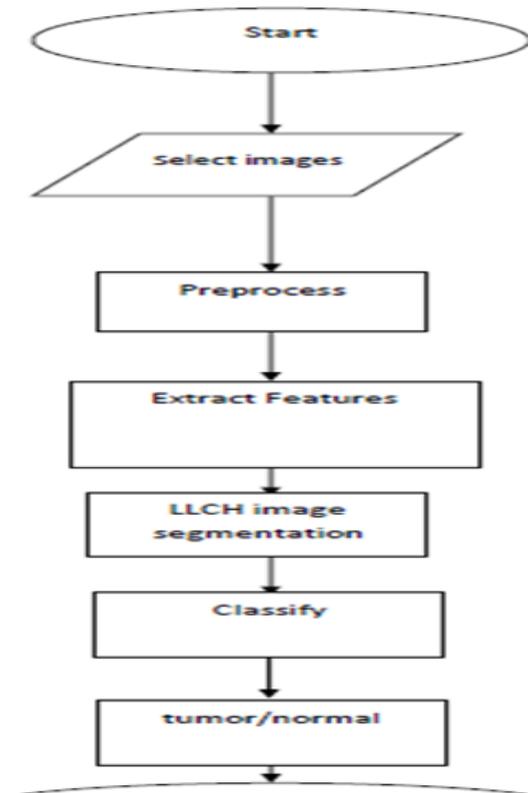


Fig 1. A flow chart of the proposed method

2. Proposed Methodology

A flowchart of the proposed method is shown in Fig1. The methods contain four steps: selection of images, preprocessing, feature extraction, segmentation.

2.1. Selection of images

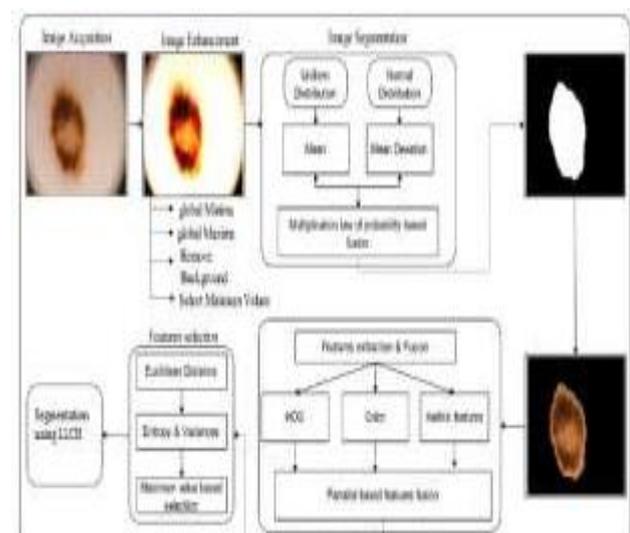


Fig 2 Block Diagram.

The skin tumor images are collected from the ISIC.

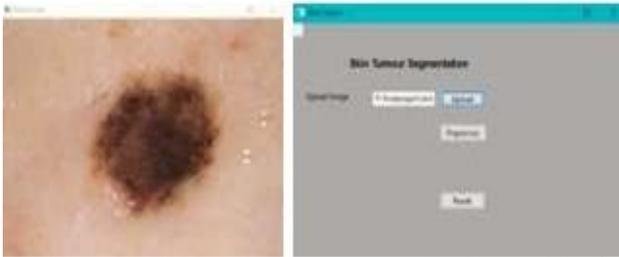


Fig 3 Input image.

2.2. Pre-processing

The input image given to the system can be obtained in any lighting condition or by using any ultra sound scanners. Hence it needs to be pre-processed. Here, the pre-processing includes the image resizing and contrast and brightness adjustment. This is done in order to compensate the non-uniform illumination in the image. These processes are done by using image processing techniques like gamma correction.

- Read the raw image
- Convert into gray scale image
- Remove noise
- Resize the shape to process the image with the size of 100X100
- apply Guassian blur
- apply gobar filter
- apply simple thresholding functions

A Grayscale image can be viewed as a single layered image. In MATLAB, a grayscale image is basically $M*N$ array whose values have been scaled to represent intensities

color images are usually represented by three channels, grayscale (black and white) images are only represented by one channel. In the case of a grayscale image, for any pixel, an intensity of 0 indicates white while an intensity of 255 indicates black (assuming each pixel is represented by one byte). We can imagine that working with one channel compared to three has advantages in memory usage and processing time.

`cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)`



Fig 4 Pre-Processing(Gray scale).

Gaussian Blur is a smoothing technique which is used to reduce noise in an image. Noise in digital images is a random variation of brightness or colour information. This degradation is caused by external sources. In Gaussian Blur, a gaussian filter is used instead of a box filter. In Python, we can use Gaussian Blur () function of the open cv library for this purpose. `cv2.GaussianBlur(src, ksize, sigmaX[, dst[, sigmaY[, borderType]]])` where,

src: Source image

dst: Output image of same size and type of source image
ksize: Size of Gaussian kernel. It should be odd and positive
sigmaX: Gaussian kernel standard deviation in x direction

sigmaY: Gaussian kernel standard deviation in y direction. If sigmaY=0, it is set equal to sigmaX

borderType:

`cv2.BORDER_CONSTANT,`
`cv2.BORDER_REPLICATE,`
`cv2.BORDER_REFLECT,`
`cv2.BORDER_REFLECT_101,`
`cv2.BORDER_TRANSPARENT,`
`cv2.BORDER_REFLECT101,`
`cv2.BORDER_DEFAULT,`
`cv2.BORDER_ISOLATED`



Fig 5 Pre-processing(gaussian blur).

A Gabor filter responds to edges and texture changes. When we say that a filter responds to a particular feature, we mean that the filter has a distinguishing value at the spatial location of that feature (when we're dealing with applying convolution kernels in spatial domain, that is. The same holds for other domains, such as frequency domains, as well). There are certain parameters that affect the output of a Gabor filter. In OpenCV Python, following is the structure of the function that is used to create a Gabor kernel.

`cv2.getGaborKernel(ksize, sigma, theta, lambda, gamma, psi, ktype)`

ksize is the size of the Gabor kernel. If `ksize = (a, b)`, we then have a Gabor kernel of size $a \times b$ pixels. As with many other convolution kernels, ksize is preferably odd and the kernel is a square (just for the sake of uniformity). Sigma is the standard deviation of the Gaussian function used in the Gabor filter. Theta is the orientation of the normal to the parallel stripes of the Gabor function. Lambda is the wavelength of the sinusoidal factor in the above equation. gamma is the spatial aspect ratio. psi is the phase offset. ktype indicates the type and range of values that each pixel in the Gabor kernel can hold



Fig 6 Gobar filter.

Thresholding is a technique in OpenCV, which is the assignment of pixel values in relation to the threshold value provided. In thresholding, each pixel value is compared with the threshold value. If the pixel value is smaller than the threshold, it is set to 0, otherwise, it is set to a maximum value (generally 255). Thresholding is a very popular segmentation technique, used for separating an object considered as a foreground from its background. A threshold is a value which has two regions on its either side i.e. below the threshold or above the threshold. cv2.threshold(src, thresholdValue, maxVal, thresholding Tehnique) OpenCV provides different styles of thresholding and it is decided by the fourth parameter of the function. Different types are:

- cv2.THRESH_BINARY: If pixel intensity is greater than the set threshold, value set to 255, else set to 0 (black).
- cv2.THRESH_BINARY_INV: Inverted or Opposite case of cv2.THRESH_BINARY.
- cv2.THRESH_TRUNC: If pixel intensity value is greater than threshold, it is truncated to the threshold. The pixel values are set to be the same as the threshold. All other values remain the same.
- cv2.THRESH_TOZERO: Pixel intensity is set to 0, for all the pixels intensity, less than the threshold value
- cv2.THRESH_TOZERO_INV: Inverted or Opposite case of cv2.THRESH_TOZERO

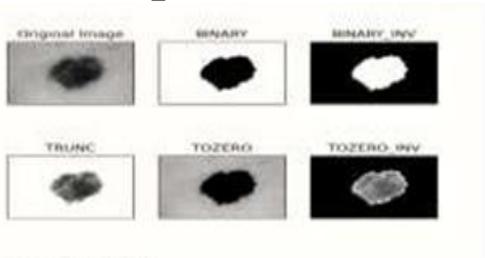


Fig no 7 Adaptive Thresholding.

2.3. Feature Extraction

The main features of the Melanoma skin Lesion are its Geometric Feature. Hence, we propose to extract the Geometric Features of segmented skin lesion. Here, we used some standard geometry features (Area, Perimeter, Greatest Diameter, Circularity Index, Irregularity Index) adopted from.11 From the Segmented image containing only skin lesion, the image blob of the skin lesion is analyzed to extract the its geometrical features. The Different Features extracted are as follows: Area (A):

Number of pixels of the lesion. Perimeter (P): Number of edge pixels.

- Read the preprocessed image
 - apply adaptive filter
 - Extract the selected features using corner harris method
 - edge detection using canny edge detection method
- Adaptive filters are commonly used in image processing to enhance or restore data by removing noise without significantly blurring the structures in the image. In many practical scenario it is observed that we are required to filter a signal whose exact frequency response is not know. A solution to such problem is an adaptive filter. A adaptive filter is one which can automatically design itself and can detect system variation in time.

An adaptive filter is defined by 4 aspects

- The signals being processed by the filter
- The structure that defines how the output signal of the filter is computed from its input signal
- The parameter within this structure that can be iteratively changed to alter the filter's input and output relationship
- The adaptive algorithm that describes how the parameters are adjusted from one time instant to the next.

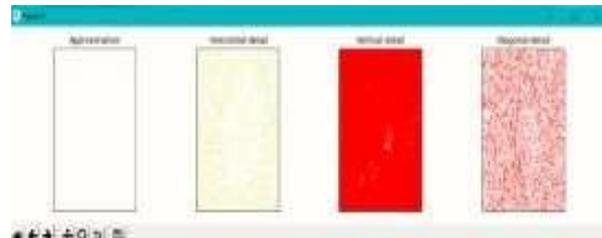


Fig 8 Adaptive filter.

Harris Corner detection algorithm was developed to identify the internal corners of an image. The corners of an image are basically identified as the regions in which there are variations in large intensity of the gradient in all possible dimensions and directions. Corners extracted can be a part of the image features, which can be matched with features of other images, and can be used to extract accurate information. Harris Corner Detection is a method to extract the corners from the input image and to extract features from the input image.

OpenCV has the function cv. cornerHarris () for this purpose. Its arguments are:

- img - Input image. It should be grayscale and float32 type.
- blockSize - It is the size of neighbourhood considered for corner detection
- ksize - Aperture parameter of the Sobel derivative used.
- k - Harris detector free parameter in the equation.



Fig 9 Feature Extraction.

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. It is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It has been widely applied in various computer vision systems. Canny has found that the requirements for the application of edge detection on diverse vision systems are relatively similar. Thus, an edge detection solution to address these requirements can be implemented in a wide range of situations. `cv2.Canny()` The general criteria for edge detection include:

- Detection of edge with low error rate, which means that the detection should accurately catch as many edges shown in the image as possible
- The edge point detected from the operator should accurately localize on the center of the edge.
- A given edge in the image should only be marked once, and where possible, image noise should not create false edges.

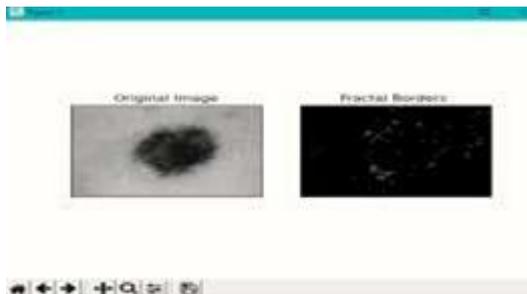


Fig 10 Canny Edge Detection.

2.4. Image Segmentation.

Initialization covering the tumor: Now, we propose experiments to test the robustness to initialization changes, from volume inside the tumor to volume covering the tumor. The aim is to confirm the results already described in the case of synthetic tumor images. LLCH-exact and LLCH-BE methods have Dice index and MAD measure quite similar to those obtained for initialization inside the tumor, with a difference less than 5%. As before, the LLCH-exact method yields the best results. The AdLL and MSCH segmentations fail in almost all cases and give very poor averaged Dice index and MAD measure. In the case of tumor 6, the segmented volume for the AdLL segmentation is unusable whereas

the result is still very good for the LLCH-exact segmentation.

Algorithm 1: LLCH-exact segmentation

```

1) Input:  $U^{n=0}$ ,  $\delta t$ ,  $\epsilon$ ,  $\alpha$  and  $I$ 
2) For:  $n = 1, \dots$ , until convergence do
3) Computation of the data attachment term, see (23):

$$U^n \leftarrow \left( U^n - \frac{T_B}{T_A} \right) \exp(2|\Omega_k|T_A\delta t) + \frac{T_B}{T_A}$$

4) Computation of the reaction term, see (29):

$$U^n \leftarrow \frac{1}{2} \mathcal{X}_{\{U^n > 1/2\}} + g_C^+ \mathcal{X}_{\{U^n > 1/2\}} + g_C^- \mathcal{X}_{\{U^n < 1/2\}}$$

5) Computation of the diffusion term, see (34):

$$U^{n+1} = \text{IFFT}(G(k)\text{FFT}(U^n))$$

6) End for
7) Output:  $U^{n+1}$ 

```

- Read the features
- apply LLCH algorithm
- segment the foreground and background portion of image
- Detect the area of tumor.
- Return tumor type.



Fig 11 LLCH Segmentation.

The watershed is a classical algorithm used for segmentation, that is, for separating different objects in an image. Starting from user-defined markers, the watershed algorithm treats pixels values as a local topography (elevation). The algorithm floods basins from the markers until basins attributed to different markers meet on watershed lines. In many cases, markers are chosen as local minima of the image, from which basins are flooded.

`cv2.watershed()`



Fig 12 Watershed Segmentation.

