Local Phase-Based Fuzzy Connectedness Segmentation of Ultrasound Images

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Abstract

Ultrasound (US) image segmentation is one of the most difficult and challenging among medical imaging modalities due to the poor signal-to-noise ratio, signal dropouts, and speckle patterns characteristic of US images. Previous methods avoided the use of purely intensity-based segmentation approaches, because of the intensity inhomogeneities present within the structures of interest. However, local phase, derived from the monogenic signal, extracts structural information from US images, being invariant to contrast. By combining different scales of the local phase, feature asymmetry can be calculated to represent edge information. This paper proposes a novel ultrasound segmentation approach based on the fuzzy connectedness framework. A new affinity function is designed to drive the segmentation algorithm using structural and edge information based on local phase, instead of intensities and intensity gradients. Quantitative and qualitative results are illustrated on US images of the fetal arm, the object of interest being the adipose tissue, which is an indicator of fetal nutrition.

1 Introduction

Ultrasound (US) image segmentation is a challenging task due to the poor signal-to-noise ratio, signal dropouts, artefacts, missing boundaries, attenuation, shadows, and speckle patterns characteristic of US images. Several approaches are available at present for segmenting *B*-mode US images [10]. Among these, the use of local phase has proven useful for a variety of image analysis tasks including segmentation [1] and boundary detection [9]. Local phase, derived from the monogenic signal [4], extracts structural image information while being invariant to contrast.

This paper introduces a novel US segmentation method based on the fuzzy connectedness framework [11], which is a region-based approach that defines the strength of local "hanging togetherness" of pixels within an image taking into account their spatial relationship and their intensity similarities within the object of interest. The method uses feature information extracted from local phase instead of image intensities, becoming invariant to contrast, and thus suitable for US image segmentation. The new approach is illustrated on US images of the fetal arm. Fetal adipose tissue in the limbs characterizes the fetal nutritional state, and its quantification could be a good indicator of fetal growth [6]. Section 2 introduces the concepts of local phase and feature asymmetry, based on the monogenic signal. Section 3 describes the novel local phase-based fuzzy connectedness segmentation approach. Qualitative and quantitative results are presented in Section 4. Conclusions are given in Section 5.

2 Local Phase and Feature Asymmetry

The monogenic signal [4] $I_M(x,y)$ of an image $I(x,y)$ generalizes the analytic signal to 2D (and higher dimensions) as $I_M(x,y) = (I_b(x,y), h_1(x,y) \otimes I_b(x,y), h_2(x,y) \otimes I_b(x,y))$, where $I_b(x,y)$ is the result of convolving $I(x,y)$ with a bandpass filter $b(x,y)$, $\otimes$ denotes the convolution operation, and h_1 and h_2 are the convolution kernels of the Riesz transforms, defined as $h_1(x,y) = x/(2\pi(x^2+y^2)^{\frac{3}{2}})$ and $h_2 = y/(2\pi(x^2+y^2)^{\frac{3}{2}})$, respectively. From $I_M(x,y)$ the local phase $\varphi(x,y)$ of $I(x,y)$ is expressed as $\varphi(x,y) = arctan(I_b/\sqrt{(h_1 \otimes I_b)^2 + (h_2 \otimes I_b)^2})$. The key choice to be made is in the selection of the bandpass filter $b(x,y)$. In the proposed method, a Gaussian Derivative filter [2] was selected. Computing the local phase at different scales, edge features can be detected at points of local phase congruency [5], by calculating the feature asymmetry as $FA = (1/N)\sum_s((\lfloor |odd_s| - |even_s| - T_s \rfloor)/(\sqrt{even_s^2 + odd_s^2} + \varepsilon))$, where $even = I_b$, $odd = (h_1 \otimes I_b, h_2 \otimes I_b)$, $\lfloor . \rfloor$ sets to zero the negative values, s represents the scale, N is the total number of scales, ε is a constant that avoids the division by zero when the local energy is small (typically $\varepsilon = 0.01$), and T_s is an orientation independent threshold that controls the spurious responses to noise at scale s [5] [9]. FA is close to 1 near boundaries and close to 0 in homogeneous regions.

3 Local Phase-Based Fuzzy Connectedness Segmentation

Fuzzy Connectedness (FC) [11] was previously used to segment tissues in the presence of intensity gradation in MR and CT images over numerous applications [7][8]. The strategy is based on a *global* fuzzy relation that assigns a strength of connectedness to every pair of pixels in an image to define objects via dynamic programming. The key step of this region-based approach relies in the definition of a *local* fuzzy relation μ_κ, called *affinity*, which defines the local "hanging togetherness" between any two adjacent pixels. If two pixels c and d are adjacent, the affinity depends on how homogeneous the region is and on how close the difference of intensity values at c and d is from the expected intensity value of the object of interest. The affinity is equal to 0 for non-adjacent pixels. The affinity values are used to define a global relation, called Fuzzy Connectedness, where the strength of connectedness between any two pixels is calculated as the largest of the strengths of all paths between c and d on the discrete image grid. Each path corresponds to a sequence of adjacent pixels starting from c and finishing in d and has a corresponding strength value, which is the smallest affinity of any pair of consecutive pixels along the path (weakest link). The fuzzy connectedness is represented as a connectivity map, where the object of interest is obtained by thresholding the image at T_{FC}. The initialisation of the method is based on manually placing one or several seeds within the object of interest.

In this paper, we adapt the FC framework to US segmentation by defining a new affinity function that uses structural and edge feature information instead of intensities. The features are derived from the measures of local phase and feature asymmetry introduced previously. The design of the affinity function is described in next. Every fuzzy subset $\mathscr{A}$ in a set is characterised by its membership function $\mu_{\mathscr{A}}$ with values in $[0,1]$. Given an image, the affinity is composed of three factors: an adjacency component μ_{α}, an object feature-based component μ_{ϕ}, and a homogeneity-based component μ_{ψ}. The adjacency component μ_{α} is a non-increasing function of the distance $\|c-d\|$ defined as $\mu_{\alpha}(c,d)=1$, if $c=d$ or $\|c-d\|=1$, and $\mu_{\alpha}(c,d)=0$ otherwise.

In the original framework, the object feature-based component is defined based on the intensities of the image, whereas the homogeneity-based component is a measure of intensity gradient [3]. By incorporating the local phase information into the object-feature based component, structural information is extracted, making the image invariant to contrast. Feature asymmetry directly gives a measure of homogeneity, since smooth regions have small values and regions near boundaries have large values (cf. Section 2). Therefore, it is natural to consider it in the definition of the homogeneity-based component. Edge information in FA is first thinned using mathematical morphology, resulting in FA_t. More specifically, let $\varphi(c)$ and $FA_t(c)$ be the local phase and thinned feature asymmetry at pixel c, respectively. The homogeneity-based component μ_{ψ} will have a high affinity in homogeneous regions and small affinity around the edges. Since FA_t is close to 0 in homogeneous regions and close to 1 near boundaries, we can express the homogeneity component as $\mu_{\psi}(c,d)=1-FA_t(c)$. The object feature-based component μ_{ϕ} takes into account characteristic features of the object of interest. In our case, we use a recent formulation [3] but directly applied to the local phase image, as follows:

$$\mu_{\phi}(c,d)=e^{-\max\{\|\varphi(c)-m\|,\|\varphi(d)-m\|\}^2/2\sigma^2}, \tag{1}$$

where m and σ are the mean and standard deviation of the object of interest, previously calculated in a training stage. The fuzzy affinity μ_{κ} is obtained by combining the affinity components [3]. One of the general forms commonly used is $\mu_{\kappa}(c,d)=\mu_{\alpha}(c,d)[\omega_1\mu_{\phi}(f(c),f(d))+\omega_2\mu_{\psi}(f(c),f(d))]$, where $f(c)$ and $f(d)$ correspond to the intensities at pixels c and d, respectively [11]. The equivalent affinity function for the new approach is expressed as $\mu_{\kappa}(c,d)=\mu_{\alpha}(c,d)[\omega_1\mu_{\phi}(\varphi(c),\varphi(d))+\omega_2\mu_{\psi}(FA_t(c))]$, where $\omega_1+\omega_2=1$, and with μ_{ψ} and μ_{ϕ} as defined previously.

4 Results

Quantitative and qualitative evaluations of the proposed approach were performed on seven cross-sectional US images of the fetal arm (Fig.1(a)), acquired between 21 and 40 weeks of gestation. The fat layer on each image was also manually segmented by a clinician 5 times. The method was implemented in Matlab, using C mex files for faster computation. Local phase (Fig.1(c)) and feature asymmetry (Fig.1(d)) were estimated as described in Section 2. T_s was obtained from statistical properties of the local phase image, and set to $T_s=0.155$. The FC framework was applied as described in Section 3. The object feature-based component of affinity was defined as in (1) using $m=m_o=1.048$ and $\sigma=3\times\sigma_o=3\times0.242$, where m_o and σ_o are the mean and standard deviation of a region of fat in the local phase image, obtained from training. The final affinity was calculated with $\omega_1=\omega_2=0.5$. The method is multiseeded with one or more seeds in the fat layer of the image used for initialisation. We applied a threshold of $T_{FC}=0.5$ to the resulting connectivity maps to get the

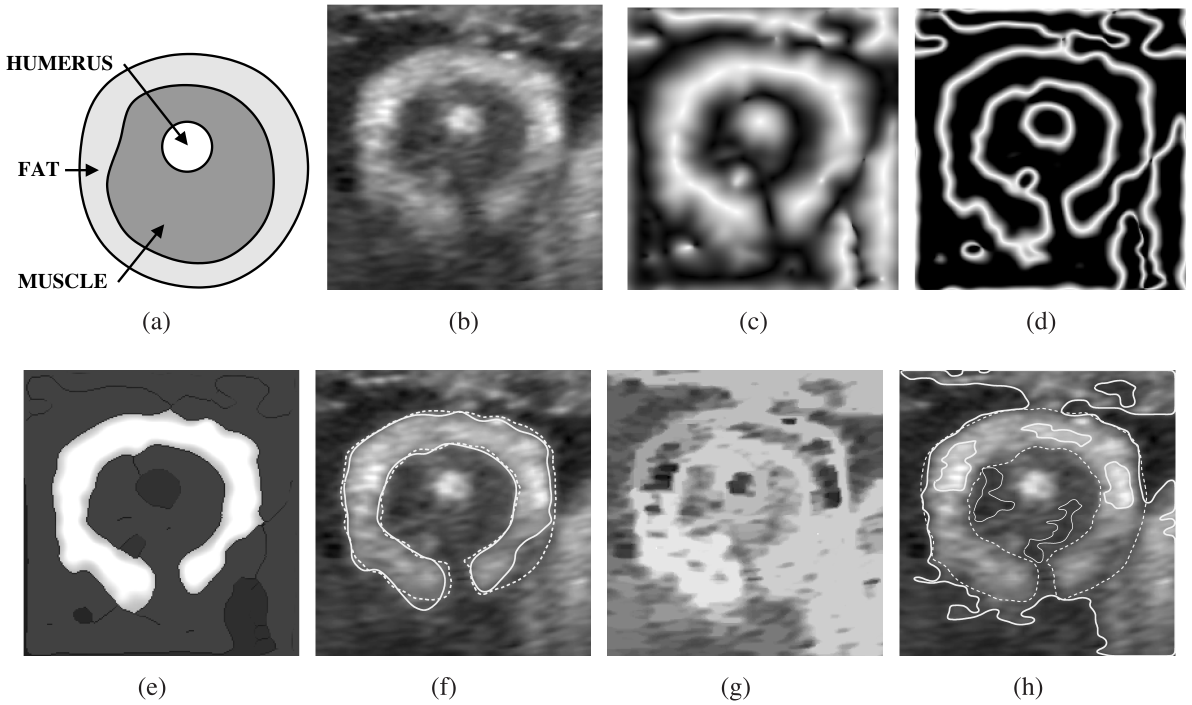

Figure 1: (a) Schematic of arm composition. (b) Ultrasound cross-sectional image of the fetal arm. (c) Local phase of (b) at $s = 25$. (d) Feature asymmetry for $N = 3$, $s = [23, 25, 27]$ and $T_s = 0.155$. (e,f) Feature-based FC connectivity map and segmentation for $T_{FC} = 0.5$. (g,h) Intensity-based FC connectivity map and segmentation for $T_{FC} = 0.75$. Dashed lines: averaged manual segmentation; Continuous lines: FC segmentation results.

final segmentations. The connectivity map and final segmentation of Fig. 1(a) are displayed in Figs.1(e-f) with the corresponding averaged manual segmentation. Figs. 1(g-h) illustrate how the original framework works in comparison to the new method. The intensity-based approach cannot overcome the inhomogeneities within the object of interest, by not detecting high intensity regions while leaking to other areas of similar intensity values. Furthermore, the lack of image standardization makes difficult to set the parameters to use for all the images in the set. This situation is avoided when using local phase, as it is contrast invariant.

The quantitative evaluation compares the segmentation results (SR) with the averaged manual segmentations, which are considered as ground truth (GT). Precision (P), Recall (R), and Dice (D) similarity were used to assess the segmentations. These are defined as: $\mathrm{P} = |\mathrm{GT} \cap \mathrm{SR}|/|\mathrm{SR}|$, $\mathrm{R} = |\mathrm{GT} \cap \mathrm{SR}|/|\mathrm{GT}|$, and $\mathrm{D} = (2 \times |\mathrm{GT} \cap \mathrm{SR}|)/(|\mathrm{GT}| + |\mathrm{SR}|)$, where $|.|$ refers to the number of elements in the set. The results show that the precision of the segmentation approach is of $93.51 \pm 1.91\%$, the recall is of $82.77 \pm 5.74\%$, and the Dice similarity is of $87.69 \pm 3.05\%$. The high precision and recall values indicate that the segmentation mainly lies within the ground truth. The Dice similarity is high and comparable to manual segmentations, which present Dice similarities between $87.14 \pm 3.68\%$ and $91.48 \pm 1.17\%$.

5 Conclusions

This paper presents a novel feature-based fuzzy connectedness segmentation method, which uses structural and edge information based on local phase, instead of intensities and intensity gradients, to drive the segmentation. This is especially useful for US images, as the method is invariant to intensity changes and relies more on the structural information. The method can be adapted to segment other objects in other applications (e.g. cardiac images) making good use of the edge and structural features. Although this paper focuses on 2D images, the method is directly applicable to higher dimensional images.

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