Research Article
Efficient Echocardiographic Image Segmentation

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In this paper, we propose an improved region-based active contour method based on the development of a novel signed pressure force (SPF) function. To obtain the required boundary, the method is applied to the echocardiographic images. Ultrasound image segmentation is particularly challenging due to speckle noise, low contrast, and intensity inhomogeneity. Because of these factors, segmenting echocardiographic images is a difficult task. All of these issues are addressed by the proposed model, which detects the true boundary without any noise. The proposed model is more robust, effective, and accurate when applied to images with weak edges and inhomogeneous intensity.

1. Introduction

Image segmentation usually involves the processing of images by a computer to detect the object that is presented in an image. Image segmentation is the most important task in image analysis. The image segmentation of echocardiographic images is strongly affected by the quality of the images. Many factors make the segmentation of echocardiographic images very difficult such as speckle noise, missing boundary due to signal dropout, and shadows. Echocardiography imaging or sonography is an important diagnostic method in medical analysis. It is significant to segment out cavities, different types of tissues, and different parts of the heart in echocardiography (sonography) for effective and correct diagnosis [1]. Segmentation of echocardiographic images is a crucial issue in medical analysis and visualization. Sonography, along with other imaging procedures such as X-rays, MRI, CT, and others, is used in medical practices to produce images of live tissues and for clinical diagnosis. Sonography has received more attention than other imaging techniques due to its advantages such as portability of the device, patient safety (noninvasive), being less expensive, and requiring less time for imaging. However, many problems arise during the segmentation of echocardiographic images.

The active contour method is one of the most popular techniques used to determine the boundary of an object in a computer view and the use of image processing. In this way, the curve shifts towards the boundary of the object under force, until stand on the real boundary of the object by reducing the force. Energy efficiency frequency depends on various factors such as bending, image gradient, and image statistical details. Functional contour models can be divided into two categories: based on edges models [2–7] and regional-based models [8–12]. Both types of models have some advantages and disadvantages, and the choice between them in the applications depends on various characteristics of images.

The active contour model uses an image gradient to create an edge acquisition function to stop the contour evolution on the boundary of an object. In addition, the region-based model uses mathematical data inside and outside the initial curve to evolve the contour toward the boundaries of the object you want. Compared to the active contour model, the regional-based model performs better on images with weak or blurred edges. The region-based model is less sensitive to the implementation of a level set and can see the boundaries of the object better.

The most popular method is based on the Mumford and Shah model [13], in the regional-based category, the active
contour that works seamlessly is Chan-Vese (CV) [9] widely used in image segmentation. Although, a regional-based model is better than an edge-based model for other features but still limited.

Therefore, such models cannot distinguish the part of objects in the image with varying intensity. To solve this problem Zhang et al. [14] have proposed a new approach based on the active contour method, using the benefits of both the CV [9] and active geodesic contour models (GAC) [2]. The majority of representative local-based models only take into account the most basic local information and disregard the spatial relationship between the core pixel and its surroundings, making it difficult to successfully segment images with intensity inhomogeneity. In reality, each pixel in an image is closely connected to its surroundings. As a result, a crucial factor that can be crucial in image segmentation is the spatial relationship between close pixels. A novel local patch similarity measure-based region-based active contour model for image segmentation is proposed by Yu et al. [15]. More background information can be found in references [15–17]. In this paper, we propose a region-based active contour method by constructing a novel signed pressure force (SPF) function based on generalized averages, a progression of the Selective Binary and Gaussian Filtering Regulated Level Set (SBGFRLS) method. The method is applied to echocardiographic images to obtain the required boundary. Since then, the model proposed in this paper has been used for echocardiographic images but is equally useful for other images.

2. Related Work

The purpose of the variational segmentation techniques is to find the boundaries of the object/region in the image by directly reducing the efficiency of the energy. These techniques propose such functions differently. For example, Geodesic Active Profile (GAC) [2] proposes the following reduction problem:

\[
\min_{C} F^{GAC}(C) = \int_{0}^{L(C)} g(|\nabla z(C(q))|)ds. \tag{1}
\]

In terms of the level set formulation the above-given energy functional obtained as follows:

\[
\frac{\partial \phi}{\partial t} = g(|\nabla z|) \left( \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) + \alpha \right) |\nabla \phi| + \nabla g \cdot \nabla \phi. \tag{2}
\]

On the other hand, the well-known Zhang et al. model combines the classical CV and GAC models in a single formulation, as shown in the following equation:

\[
spf(z(x, y)) = \frac{z(x, y) - w_1 + w_2/2}{\max\left(\left|z(x, y) - w_1 + w_2/2\right|\right)}, \quad (x, y) \in \Omega, \tag{3}
\]

where \(w_1, w_2\) are average intensities defined by the following equation:

\[
w_1 = \frac{\int_{\Omega} zH_e \, dx \, dy}{\int_{\Omega} H_e \, dx \, dy}, \quad w_2 = \frac{\int_{\Omega} z(1 - H_e) \, dx \, dy}{\int_{\Omega} (1 - H_e) \, dx \, dy}. \tag{4}
\]

Finally, the following evolution equation is extracted.

\[
\frac{\partial \phi}{\partial t} = aSpf(z(x, y))|\nabla \phi|, \quad (x, y) \in \Omega. \tag{5}
\]

The SBGFRLS model [14] is capable of overcoming the weaknesses of the GAC and CV models, but it is still unsuitable for echocardiographic images. So here is another Spf function \(Spf_{KS}\) proposed by Saini in [18], defined by the following equation:

\[
Spf_{KS}(z(x, y)) = \frac{((w_1 * w_2) * ((z(x, y)) - w_1 + w_2/2))}{\max(\left(\left((w_1 * w_2) * ((z(x, y)) - w_1 + w_2/2)\right)\right))} \tag{6}
\]

The level set equation for the \(Spf_{KS}\) is as follows:

\[
\frac{\partial \phi}{\partial t} = aSpf_{KS}(z(x, y))|\nabla \phi|, \quad (x, y) \in \Omega. \tag{7}
\]

3. The Proposed Model

By Jin model [19], we proposed \(F^{NEW}\) to formulate a new SPF function. Let \(z : \Omega \rightarrow \mathbb{R}\) be an input image and let \(C\) be a closed curve, the energy functional for our proposed model is as follows:

\[
F^{NEW}(C, w_1, w_2) = \int_{\Omega} \frac{(z - w_1)^2}{w_1} \, dx \, dy + \int_{\Omega} \frac{(z - w_2)^2}{w_2} \, dx \, dy, \tag{8}
\]

where \(w_1\) and \(w_2\) are the corresponding intensity averages of inside and outside \(C\), respectively. In terms of level set formulation, the proposed model formulate as follows:

\[
F^{NEW}(\phi, w_1, w_2) = \int_{\Omega} \frac{(z - w_1)^2}{w_1} \, H(\phi) \, dx \, dy + \int_{\Omega} \frac{(z - w_2)^2}{w_2} \, (1 - H(\phi)) \, dx \, dy, \tag{9}
\]

where \(H(\cdot)\) is the Heaviside function, defined by the following equation:

\[
H(x) = \begin{cases} 1 & \text{if } x \geq 0, \\ 0 & \text{if } x < 0. \end{cases} \tag{10}
\]

The proposed energy functional minimizing concerning \(w_1\) and \(w_2\), and fixed \(\phi\) gives the following results:
\[
\frac{\partial F^{\text{NEW}}}{\partial w_1} = 0, \\
\Rightarrow \int_{\Omega} \left( \frac{-(z - w_1)^2}{w_1^2} - \frac{2(z - w_1)}{w_1} \right) H(\phi) \, dx \, dy = 0, \\
\Rightarrow \int_{\Omega} \left( \frac{-z^2 - w_1^2 + 2zw_1}{w_1^2} - \frac{2(z - w_1)}{w_1} \right) H(\phi) \, dx \, dy = 0, \\
\Rightarrow \int_{\Omega} \left( \frac{-z^2 + w_1^2}{w_1^2} \right) H(\phi) \, dx \, dy = 0, \\
\Rightarrow w_1^2 \int_{\Omega} H(\phi) \, dx \, dy = \int_{\Omega} z^2 H(\phi) \, dx \, dy, \\
\Rightarrow w_1^2 \int_{\Omega} H(\phi) \, dx \, dy = \int_{\Omega} H \, dx \, dy. \\
\tag{11}
\]

Similarly,

\[
w_2 = \frac{\int_{\Omega} z^2 (1 - H) \, dx \, dy}{\int_{\Omega} (1 - H) \, dx \, dy}. \\
\tag{12}
\]

So, the averages \(w_1\) and \(w_2\) of the proposed model are

\[
w_1 = \sqrt{\frac{\int_{\Omega} z^2 H \, dx \, dy}{\int_{\Omega} H \, dx \, dy}}, \\
w_2 = \sqrt{\frac{\int_{\Omega} z^2 (1 - H) \, dx \, dy}{\int_{\Omega} (1 - H) \, dx \, dy}}. \\
\tag{13}
\]

Now, by keeping \(w_1\) and \(w_2\) fixed, we minimize the energy functional \(F^{\text{NEW}}\) with respect to \(\phi\), we obtain the following equation:

\[
\frac{\partial F^{\text{NEW}}}{\partial \phi} = 0, \\
\Rightarrow \left( \frac{z - w_1}{w_1} \right) \delta (\phi) + \left( \frac{z - w_2}{w_2} \right) (-\delta (\phi)) = 0, \\
\Rightarrow \delta (\phi) \left[ \left( \frac{z - w_1}{w_1} \right)^2 - \left( \frac{z - w_2}{w_2} \right)^2 \right] = 0. \\
\tag{14}
\]

From the solution of the Euler–Lagrange equation, we obtain the evolution equation, as follows:

\[
\frac{\partial \phi}{\partial t} = \delta (\phi) \left[ \left( \frac{z - w_1}{w_1} \right)^2 - \left( \frac{z - w_2}{w_2} \right)^2 \right], \\
\tag{15}
\]

where \(\delta (\cdot)\) is the generalized Dirac delta function defined by the following equation:
\( \delta(x) = \frac{d(H(x))}{dx} = \begin{cases} 0 & \text{if } x \neq 0, \\ \infty & \text{if } x = 0. \end{cases} \) (16)

The proposed global signed pressure force (Gspf) function is defined as follows:

\[
Gspf(x, y) = \frac{(x, y)^2}{w_1 \cdot w_2 - 1} \max(\{(x, y)^2/w_1 \cdot w_2 - 1\}) \] (17)

where \( w_1 \) and \( w_2 \) are the intensity averages. The importance of the new Spf function described in (17) can be explained by referring to figure 1, which shows that

\[
\text{Min}(z(x, y)) \leq w_1, w_2 \leq \text{Max}(z(x, y)). \] (18)

3.1. Generalized Global Signed Pressure Force Function.

To get better segmentation results, we have used the generalized averages for the proposed Gspf function.

The Gspf function based on generalized averages is denoted by \( Gspf_\beta \), and is defined as follows:

\[
Gspf_\beta(x, y) = \frac{(x, y)^2/G_{w_1} \cdot G_{w_2} - 1} \max(\{(x, y)^2/G_{w_1} \cdot G_{w_2} - 1\}) \] (19)

\((x, y) \in \Omega\).

Thus, replacing the Spf function in equation (5) by \( Gspf_\beta \) function, defined in (19) yields the following evolution equation:
\[
\frac{\partial \phi}{\partial t} = a Gsp(x, y) \sum_{i,j} |\nabla \phi|, \quad (x, y) \in \Omega.
\] (20)

4. Tests

In this section, we compare some experimental results of the new $Gsp(x, y)$ model to those of the SBGFRLS [14] and KS models [18]. These results demonstrate that the proposed model is accurate and effective in handling echocardiographic images with intensity inhomogeneity, noise, and low contrast, or that do not have piecewise constant intensities, whereas the compared models only work well for so many images. Figure 2 shows the results of echocardiographic image boundary detection using the SBGFRLS model. It is clear from this that none of the six cases provide satisfactory boundaries. Figure 3 the results obtained here are superior to those obtained by the SBGFRLS model. The KS model, on the other hand, is incapable of correctly detecting the boundaries of all images. As a result, locating the endocardium correctly is difficult. Figure 4 demonstrates that the proposed model detects all endocardium and chamber boundaries accurately. The proposed model outperforms as compared to the SBGFRLS and KS models in terms of efficiency and correctness.

5. Conclusion

In this paper, we proposed a new region-based-active contour model based on a new Generalized Global Signed Region Pressure Force ($Gsp(x, y)$) function that combines the benefits of both edge-based and region-based models. As a result, the proposed model outperforms traditional region-based methods in segmenting images with weak and blurred edges. To demonstrate its robustness and effectiveness, the proposed method is applied to the simultaneous segmentation of 2D real echocardiographic images with intensity inhomogeneity. The model automatically and efficiently modulates the signs of the pressure forces inside and outside the contour. Finally, using echocardiographic images with intensity inhomogeneity, the comparison is made with other active contour methods that use traditional Spf functions formulated by the CV model [9]. It demonstrates that, unlike previously developed Spf-based active contour methods, the proposed method can segment images with intensity inhomogeneities.

Data Availability

The data that support the findings of the study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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