Active Contours Using Harmonic Global Division Function

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Abstract—**This paper presents the region-based active contours method based on the harmonic global signed pressure force (HGSPF) function. The proposed formulation improves the performance of the level set method by utilizing intensity information based on the global division function, which has the ability to segment out regions with higher intensity differences. The new energy utilizes harmonic intensity, which can better preserve the low contrast details and can segment complicated areas easily. A Gaussian kernel is adjusted to regularize level set and to escape an expensive reinitialization. Finally, a set of real and synthetic images are used for validation of the proposed method. Results demonstrate the performance of the proposed method, the accuracy values are compared to previous state-of-the-art methods.**

Keywords-image segmentation; active contours; HGSPF function

I. INTRODUCTION

Segmentation is a technique to isolate particular image regions having a variety of uses in image processing and computer vision [1]. Images with feeble edges, noise, and obscured boundaries have some regarding this aspect. In manual segmentation, human mistakes can deliver more false results, so, a computer-based system is required, which can bolster experts and radiologists to partition accurate tumor muscles or true regions [2]. A few techniques have been proposed regarging the image segmentation issue. Authors in [3] proposed an underlying contour based procedure for separating objects in an image. Active contour image segmentation is a strategy, in which an implicit curve is deformed using some minimization procedure until it achieves the ideal boundary. There are two significant groupings of active contour techniques, which are edge based strategies [4-6] and region based techniques [7-14]. Edge based procedures set up an edge force by using the edge data of an image, which turn towards the required boundaries. These models do not accomplish right segmentation on images with weak and obscured boundaries. Region based methods use image pixel information and develop region based force terms, which divide the pixels inside an image. The work in [9] is viewed as the most utilized model for global region based segmentation. This strategy is not suitable for unclear boundaries and images which have intense pixel contrast and complicated background variations. To minimize such problems, authors in [8] proposed an altered global region based technique, which utilizes four intensity means for pixel regions across the image. Due to the impact of global division algorithim, this technique enhances segmentation. Authors in [7] proposed a strategy which utilizes global pixel data from [9] and builds up a SPF (Signed Pressure Force) function. Also, it utilizes a Gaussian kernel to regularize a level set function in each cycle. A modified SPF method was formulated in [15] using harmonic means instead of arithmetic. This method reduces the approximation error of the previous methods. Motivated by [7, 8, 15], we propose a novel harmonic global signed pressure force (HGSPF) function. HGSPF function utilizes global division and harmonic intensity information in its design. It yields better results over images having complicated intensity information and/or low contrast. Moreover, a Gaussian filter has been induced to regularize level set and to overcome the need of level set reinitialization. The proposed strategy is validated over synthetic and real images. The results are compared in terms of accuracy, which indicates the effectiveness of the proposed method compared to previous state of the art methods.

II. RELATED WORK

Authors in [9] proposed a mainstream global intensity technique in the light of [16]. This technique relies upon

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gradient based segmentation techniques. Lets suppose an image $I:\Omega\subset R$ with a level set $\phi:\Omega\subset R$ and C is a curve for level set: the following formulations are proposed:

$$E_{CV}(u,c_2,C)=\lambda_1\int_\Omega |I(x)-u_1|^2 M_1 dx + \lambda_2\int_\Omega |I(x)-u_2|^2 M_2 dx + \mu\text{Length}(C)+v\text{Area}(in(C)) \quad (1)$$

where μ, v, λ_1 and $\lambda_2 > 0$ are constants. Length term regularizes the contour C. M_1 and M_2 are defined as:

$$M_1 = H_\epsilon(\phi(x)) \quad (2)$$

$$M_2 = (1-H_\epsilon(\phi(x))) \quad (3)$$

where $H_\varepsilon(\phi)$ is a Heaviside function is defined as:

$$H_\varepsilon(\phi)=\frac{1}{2}\left(1+\frac{2}{\pi}\arctan\left(\frac{\phi}{\varepsilon}\right)\right) \quad (4)$$

ε accomplishes the smoothness of the Heaviside function. u_1 and u_2 are statistical means of an image inside and outside of curve C respectively, which are explained as:

$$u_1=\frac{\int_\Omega I(x)M_1 dx}{\int_\Omega M_1 dx} \quad (5)$$

$$u_2=\frac{\int_\Omega I(x)M_2 dx}{\int_\Omega M_2 dx} \quad (6)$$

Minimizing (1) by gradient descent [17], we achieve the following variational formulation:

$$\frac{\partial\phi}{\partial t}=\left(-\lambda_1(I-u_1)^2+\lambda_2(I-u_2)^2+\mu\text{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)-v\right)\delta_\varepsilon(\phi) \quad (7)$$

where $\delta_\varepsilon(\phi)$ is a Dirac function defined as:

$$\delta_\varepsilon(\phi)=\frac{\varepsilon}{\pi(\phi^2+\varepsilon^2)} \quad (8)$$

where μ controls the smoothness of the level set function, v is utilized to pace contour evolution and λ_1, λ_2 are constants for the inner and outer force of the contour. It is considered as a sound technique for segmenting images with noisy and obscured regions. However, this strategy is not fit for images which have higher intensity distinction or images with convoluted intensity information in the background.

To overcome this obstacle, authors in [8] proposed an enhanced global division intensity term, which can segment complex intensity regions inside homogenous images. Global division function is joined in their energy definition in a new region based term. This strategy can segment objects with enormous distinction of intensity regions. They proposed the following formulations:

$$\begin{aligned}E_{MIN}(\phi,u_1,u_2,w_{11},w_{12},w_{21},w_{22}) = \\ \int_\Omega H(I(x)-u_1)(I(x)-w_{11})^2 M_1 dx \\ +\int_\Omega (1-H(I(x)-u_1))(I(x)-w_{12})^2 M_1 dx \\ +\int_\Omega H(I(x)-u_2)(I(x)-w_{12})^2 M_2 dx \\ +\int_\Omega (1-H(I(x)-u_2))(I(x)-w_{22})^2 M_2 dx\end{aligned} \quad (9)$$

where $H(I(x)-u_i),(i=1,2))$ is a global division intensity function. Instead of considering two intensity terms, this procedure considers four intensity terms, two inside and two outside the contour.

The technique developed in [9] cannot authentically capture an object with bigger intensity distinction. Figure 1 displays the segmentation of one complex image for both methods.

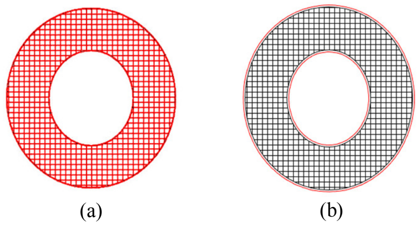


Fig. 1. Image segmentation on images having intensity difference (a) Chan-Vese [9], (b) [8]

An active contour strategy with respect to ACSLG (active contour with selective local and global) technique was proposed in [7] as a blend of GAC [18] and [9] methods. In this model, a region based SPF term was proposed, which can perfectly stop the curve at weak or fuzzy edges. This model can capture outside regions if initialized inside and capture inside regions if initilzed outside the object. In addition, this model uses the Gaussian kernel to regularize the level set dimension set. They propose the energy term as:

$$\frac{\partial\phi}{\partial t}=spf(I(x))(|\nabla\phi|)\left(\text{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+\alpha\right) + \nabla spf(I(x))\nabla\phi \quad (10)$$

A novel SPF force term is introduced:

$$spf(I(x))=\frac{I(x)-(u_1+u_2)/2}{\max(|I(x)-(u_1+u_2)/2|)} \quad (11)$$

where u_1 and u_2 are global intensities computed from the given image defined in (5) and (6) correspondingly.

More recently, authors in [15], summed up the Chan-Vese [9] energy formulation and proposed another exceptional case.

The new energy in this method reduces the estimate error and can more effectively safeguard the regions with minute difference between ROIs and background, hence this method can viably segment images, particularly with low contrast. Authors came up with a two-phase harmonic approximation in their energy formulation instead of the traditional arithmetic intensity approximations in [9]. They proposed the following general form of energy function:

$$\begin{aligned} E(u,C) &= \lambda_1 \int_\Omega |\mathrm{f}(I(x)) - f(u_1)|^2 M_1 dx \\ &+ \lambda_2 \int_\Omega |\mathrm{f}(I(x)) - f(u_2)|^2 M_2 dx \\ &+ \mu \mathrm{Length}(C) + v\mathrm{Area}(in(C)) \end{aligned} \tag{12}$$

where f is reciprocal harmonic mean average i.e., $f(x)=1/x$. The harmonic mean intensities are usually less than one, while the traditional means u_1 and u_2 in (1) are greater than one. So, in this case, this method penalizes the approximation error in a lighter way than Chan-Vese method, which does this in a stronger way. For low contrast images u_1 and u_2 remain close to each other, which makes the contour stationary and does not capture the required boundaries. Therefore, this method can get image boundaries in low contrast images.

III. PROPOSED METHOD

The following harmonic energy function is proposed:

$$\begin{aligned} & E_{MIN}(\phi, u_1, u_2, w_{11}, w_{12}, w_{21}, w_{22}) = \\ & \int_\Omega H(f(I(x)) - f(u_1))(f(I(x)) - f((w_{11})))^2 M_1 dx \\ & + \int_\Omega (1 - H(f(I(x)) - f(u_1)))(f(I(x)) - f(w_{12}))^2 M_1 dx \\ & + \int_\Omega (1 - H(f(I(x)) - f(u_2)))(f(I(x)) - f(w_{22}))^2 M_2 dx \\ & + \int_\Omega H(f(I(x)) - f(u_2))(f(I(x)) - f(w_{12}))^2 M_2 dx \end{aligned} \tag{13}$$

where $H(f(I(x)) - f(u_i)), (i = 1,2)$ is a harmonic global division function. In (13), we take four harmonic means, two for each side of the contour. After minimizing the above problem, we get the following new harmonic solutions:

$$w_{11} = \frac{\int_\Omega (H(f(I(x)) - f(u_1)))M_1 dx}{\int_\Omega (H(f(I(x))) - f(u_1)))f(I(x))M_1 dx} \tag{14}$$

$$w_{12} = \frac{\int_\Omega (1 - Hf((I(x)) - f(u_1)))M_1 dx}{\int_\Omega (1 - H(f((I(x))) - f(u_1)))f(I(x))M_1 dx} \tag{15}$$

$$w_{21} = \frac{\int_\Omega (Hf((I(x)) - f(u_2)))M_2 dx}{\int_\Omega (H(f((I(x))) - f(u_2)))f(I(x))M_2 dx} \tag{16}$$

$$w_{22} = \frac{\int_\Omega (1 - H(f((I(x)) - f(u_2))))M_2 dx}{\int_\Omega (1 - H(f((I(x)) - f(u_2)))f(I(x))M_2 dx} \tag{17}$$

Lets take an image $I : \Omega \subset R$, a level set $\phi : \Omega \subset R$, and a closed contour C equivalent to a zero-level set: $C = \{x \in \Omega | \phi(x) = 0\}$. The following energy term is proposed:

$$E_{HGSPF}(\phi) = \lambda L_{HGSPF}(\phi) + vA_{HGSPF}(\phi) + \alpha P(\phi) \tag{18}$$

where $L_{hspf}(\phi)$ is the length and $A_{hspf}(\phi)$ is the area terms respectively. These terms are calculated as:

$$L_{hgspf}(\phi) = \int_\Omega hgspf(I)\delta_\varepsilon(\phi)|\nabla\phi|\, dx \tag{19}$$

$$A_{hgspf}(\phi) = \int_\Omega hgspf(I)H_\varepsilon(-\phi)dx \tag{20}$$

where $hgspf(I)$ is a HGSPF function which is defined as:

$$HGSPF(I) = \frac{(I(x) - HG)}{\max(|I(x) - HG|)} \tag{21}$$

where HG is a newly developed two-phase harmonic global fitted image model which is characterized as:

$$HG = \frac{4w_{11}w_{12}w_{21}w_{22}}{w_{12}w_{21}w_{22} + w_{11}w_{21}w_{22} + w_{11}w_{12}w_{22} + w_{11}w_{12}w_{21}} \tag{22}$$

where w_{11}, w_{12}, w_{21} and w_{22} are the intensity means described in (14)-(17). By the calculus of variations [17], the final level set of an energy functional E_{HGSPF} in (27) can be defined as:

$$\frac{\partial\phi}{\partial t} = \lambda.\mathrm{div}\left(hgspf(I)\frac{\nabla\phi}{|\nabla\phi|}\right)\delta_\varepsilon(\phi) + vhgspf(I)\delta_\varepsilon(\phi) \tag{23}$$

The HGSPF term has the incentive to modulate its sign within the [-1,1] region depending on the initialization of the curve. If it is placed outside of an object, the curve deforms inwards and if placed inside, the curve expands in the outward direction. Traditional level set methods use some initialization techniques to maintain the level set ϕ as signed distance function (SDF). The proposed method totally discards the costly re-initialization strategy by utilizing the penalization term from LSEWR method [9]. The initialization function for our method is defined as:

$$\phi(x, t=0) = \begin{cases} -\rho & x \in \Omega_0 - \partial\Omega_0 \\ 0 & x \in \partial\Omega_0 \\ \rho & x \in \Omega - \Omega_0 \end{cases} \tag{24}$$

where ρ>0 is constant. The steps of the proposed method are:

1. Initialize ϕ by ϕ_0 using (24) at t=0.

2. Compute $w_{11}(\phi)$, $w_{12}(\phi)$, $w_{21}(\phi)$ and $w_{22}(\phi)$ using (14), (15), (16) and (17) respectively.

3. Compute $HGSPF(I)$ from (21).

4. Solve the PDE of ϕ using (23).

5. If the result does not change then terminate, otherwise, move to step 2 and repeat.

IV. EXPERIMENTAL RESULTS

The experiments were performed on MATLAB 8.0 installed in a PC running Windows 10, with Quad Core CPU 2.4GHZ and 8GB RAM. In this paper, these parameters were selected manually: λ=1, μ=200/2552, ν=15, α=0.2/Δt, Δt=1.0, K=5, ρ=4, ε=1.5 and s=1.5. Initially, the method was tested on some simple images, which are demonstrated in Figure 2.

Figure 3 delineates segmentation utilizing the proposed method and some previous methods. Results demonstrate that the proposed technique accomplishes the required segmentation results correctly. Chan-Vese [9] had also segmented some noise, while LBF neglected to accomplish the ideal segmentation results.

Figures 4-5 exhibit the results of the Chan-Vese [9], LBF [21, 22] and the proposed strategy on mammograms taken from the mini MIAS database [20]. The results demonstrate that tumor segmentation has been efficiently segmented by the proposed technique while the other methods delivered inadmissible outcomes.

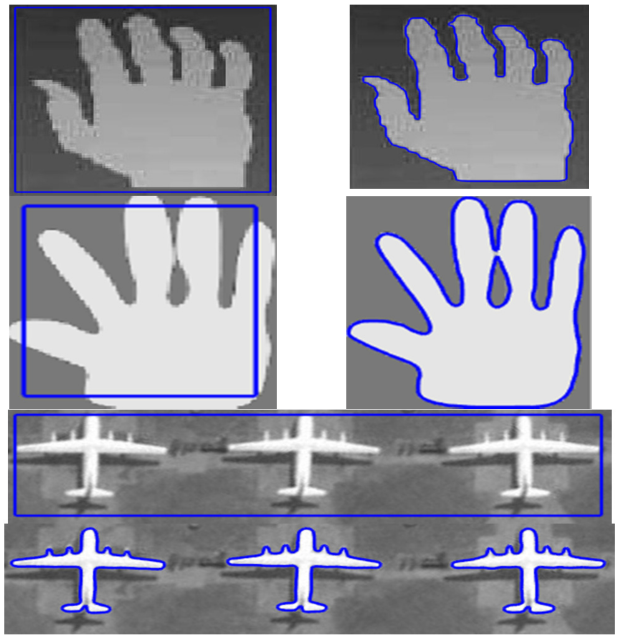
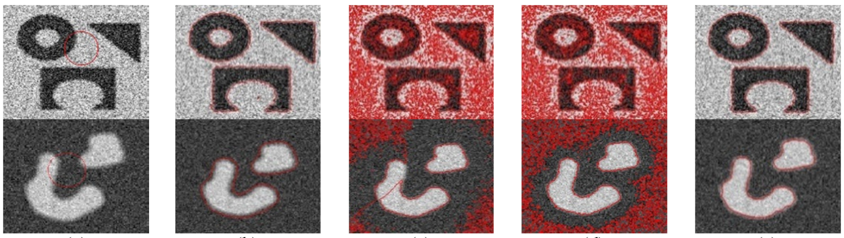
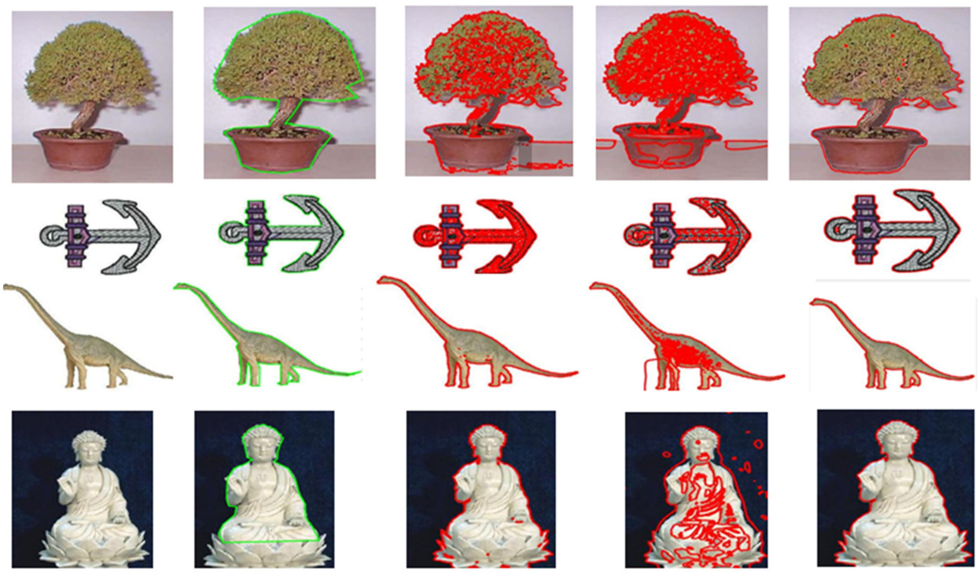


Fig. 2. Proposed method segmentation results and their initialization



(a) (b) (c) (d) (e)

Fig. 3. Noisy image segmentation results: (a) Images and initial contours, (b) Chan–Vese, (c) LBF, (d) LCV and (e) proposed



(a) (b) (c) (d) (e)

Fig. 4. Segmentations result on a real set of images, (a): original images, (b) ground truth (c) Chan-Vese, (d) LBF, (e) proposed

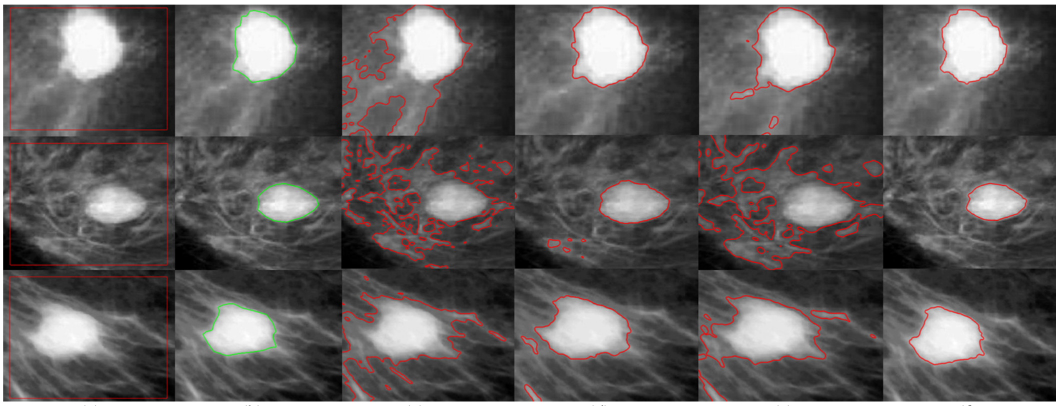


Fig. 5. Quantitative comparison on mammogram images: (a) Original images, (b) ground truth. (c) [9], (d) [7], (e) [19], (f) proposed

V. QUANTITATIVE COMPARISON

For quantitative results, we used images taken from a publically accessible dataset [20] (Figure 5). The results exhibit that the proposed strategy improved the results of previous methods. We have utilized an accuracy metric to validate nature of our outcomes. The formulation of the metric is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (34)$$

where TP (true positive) stands for the segmented region, TN (true negative) for the accurately unsegmented regions, FP (false positive) stands for regions erroneously considered as true and FN (false negative) are the undetected tumor areas. Table I demonstrates the accuracy metric study of proposed technique and previous methods. We can see that the accuracy of the proposed methodology is essentially improved in comparison with the previous methods.

TABLE I. ACCURACY COMPARISON

	Method			
Image	**[9]**	**[7]**	**[19]**	**Proposed**
Row 1	0.5368	0.9587	0.7247	0.9628
Row 2	0.6856	0.7456	0.7124	0.9698
Row 3	0.5789	0.8321	0.2354	0.9321

VI. CONCLUSION

A novel HGSPF (harmonic global signed pressure force function) was presented in this paper. A global division function was used to approximate intensity means inside image regions. With the incursion of global intensity means and harmonic function, the proposed technique brought better outcomes in terms of accuracy, than the previous methods. Gaussian filter was adapted to eliminate an expensive reinitialization and to regularize level set. Finally, quantitative analysis demonstrated the effectiveness of the proposed method.

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