

Effective Image Segmentation using Composite Energy Metric in Levelset Based Curve Evolution

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RECEIVED ON 22.12.2017 ACCEPTED ON 12.02.2018

ABSTRACT

Accurate segmentation of anatomical organs in medical images is a complex task due to wide inter-patient variability and several acquisition dependent artefacts. Moreover, image noise, low contrast and intensity inhomogeneity in medical data further amplifies the challenge. In this work, we propose an effective yet simple algorithm based on composite energy metric for precise detection of object boundaries. A number of methods have been proposed in literature for image segmentation; however, these methods employ individual characteristics of image including gradient, regional intensity or texture map. Segmentation based on individual features often fail for complex images, especially for medical imagery. Accordingly, we propose that the segmentation quality can be improved by integrating local and global image features in the curve evolution. This work employs the classic snake model aka active contour model; however, the curve evolution force has been updated. In contrast to the conventional image-based regional intensity statistics, the proposed snake model evolves using composite image energy. Hence, the proposed method offers a greater resistance to the local optima problem as well as initialization perturbations. Experimental results for both synthetic and 2D (Two Dimensional) real clinical images are presented in this work to validate the performance of the proposed method. The performance of the proposed model is evaluated with respect to expert-based manual ground truth. Accordingly, the proposed model achieves higher accuracy in comparison to the state-of-the-art region based segmentation methods of Lankton and Yin as reported in results section.

Key Words: Active Contour Model, Level Set Evolution, Composite Energy.

1. INTRODUCTION

Precise segmentation in medical data is very important as it facilitates clinicians to identify anatomical abnormalities effectively. Segmentation algorithms often rely on image features including intensity, contrast, or geometrical characteristics to distinguish different objects, however shape complexity

of anatomical structures often makes task challenging. A simple benchmark for object differentiation in an image is edge or discontinuity measure as defined in Equation (1). Edge-based segmentation works fine for images having strong boundaries but ambiguous object boundaries are often over segmented as weak edges are surpassed during evolution.

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$$|g(x, y)| = \sqrt{\nabla I_x^2 + \nabla I_y^2} \quad (1)$$

Moreover, edge based segmentation generally involves post processing for intelligent placement of new points and removal of spurious points to obtain closed object boundaries. In contrast, Region based methods have shown more potential for image segmentation due to resistance against weak edges. Segmentation quality depends upon clustering criteria used to establish homogeneous regions. Conventionally pixel intensity values are used in combination with neighborhood information for region based segmentation. Consequently, N homogeneous regions in an image “I” are defined as follows:

$$R_1 \cup R_2 \cup R_3 \cup \dots \cup R_n = I \quad (2)$$

where R_1, \dots, R_n represent distinct regions in the image. It is important to mention that depending upon the nature and complexity of the imaging modality, a number of image features can be combined i.e. intensity and geometric for effective segmentation of object. In addition to the conventional edge and region based methods, some other techniques for object segmentation include threshold, clustering and watershed interpretation. Moreover, the idea of deformable contours is also used frequently which evolves based of partial differential equations to detect object boundaries.

2. RELATED WORK

Majority of the existing segmentation algorithms are based on active contour models that evolve initial curve iteratively to catch true boundary of objects. Two standard representations for evolving contour include parameterized snakes and level set formulation. Level set formulation is preferred in image segmentation due to

flexibility against topology changes during evolution whereas parametric curves are preferred for fast but simple evolutions. Kass et. al. [1] correlated the concept of image segmentation with energy optimization for the first time in early 90s. Accordingly, the explicit Lagrangian formulation of curve energy pushes the evolving contour towards object boundaries such that energy becomes optimal at object boundaries. Total energy of the evolving curve is based on both curve inherent features and image characteristics as follows:

$$E = \int [E_{int}(V(s)) + E_{image}(V(s)) + E_{cons}(V(s))] ds \quad (3)$$

where internal energy is intrinsic property of curve based on elasticity and stiffness and external energy is derived from image for instance gradient strength and external constraints can be added employing prior knowledge to control the behavior of curve. Image based curve driving force E_{image} plays vital role in successful delineation as cost function for energy optimization is based on image properties. Methods reported in [1,2,3] rely on image based edge strength for image segmentation. The efficiency of the edge based segmentation is directly associated with the nature of the image. For a clean image having sharp object boundaries, the edge based segmentation performs exceptionally well. In contrast, for weak edges and noise-affected images, edge-based segmentation often fails due to ambiguous intensity at object boundaries. Likewise, a number of algorithms have been proposed that rely on region based intensity statistics for image segmentation. Chan and Vese [4], Yezzi et. al. [5] and Roussan [6] reported successful implementation of region based segmentation. However, intensity inhomogeneity in medical images often leads to over segmentation in these methods as they rely on assumption of piecewise constant intensity which is

often violated in medical data. To address the intensity variations in medical images, an efficient framework was proposed by Lankton and Tannenbaum [7]. Proposed framework named LRBAC (Localized Region Based Active Contours) demonstrates successful segmentation for heterogeneous images however the computational cost increases in relation to localization scope. Consequently, computational burden can be addressed by intelligent initialization and selection of localization radius but in practice it is difficult to place smart initializations for complex medical vasculature in presence of anomalies. A computationally robust model for heterogeneous imagery was proposed by Li et. al. [8,11] where the localized information was used at adjustable scales but the associated limitation of extreme dependency on initial mask demands certain prior information. Yin and Liatsis [9] proposed an efficient technique for hybrid energy based segmentation. The authors started with the assumption of constant background to obtain a bimodal image in first stage. Subsequently obtained bimodal image was approximated with Gaussian distribution to construct CDF (Cumulative Distribution Function) based explicit label image that differentiates object from background. Based on CDF background pixels were shifted in range of [-1, 0] whereas object was placed in [0, +1] interval in label image. Due to underlying supposition of constant background, this method fails to handles intensity variations in variety of medical images. Specifically, intensity shift in background leads erroneous labels that start pulling back the contour instead of pushing to object boundaries. By considering the shortcomings of Yin's method [9], we propose to integrate the global behavior of image in terms of intensity continuity map. Edge based global force dominates in case of vague initializations and pushes curve rapidly towards true edges by beating false optimal solutions whereas

localized intensity can adjust contours accurately on boundary by resisting intensity variations. Consequently, the evolving contour moves under the weighted influence of edge strength and regional statics to ensure optimal solution. The contribution of global force can be regulated by adjusting weight depending upon the nature of image, noise and initial placement of mask.

3. PROPOSED METHOD

In this section, we propose segmentation based on the composite energy metric for precise detection of object boundaries in presence of intensity shifts. Localized statistics based component of composite energy resists intensity inhomogeneity whereas global component confirms attraction towards object boundaries. Consequently, the integrated use of two terms in curve evolution leads to precise detection of object boundaries as total curve force can be computed as:

$$F_{\text{composite}} = (F_{\text{local}}) + \beta.F_{\text{(global)}}$$

Here F_{local} and F_{global} represent image-based local and global energy terms and β is constant, regulating the influence of the global energy component in overall curve evolution. A high value of β leads to capture sharp edges, whereas a low value minimizes the global influence. In this work, β has been set equal to 0.5 based on empirical evidence.

3.1 Modelling Local Energy

As an extension of Mumford and Shah [10] piecewise smoothness assumption, Chan and Vese proposed region based active contour model for image segmentation as defined in Equation (4):

$$F(c1, c2, C) = \lambda \text{length}(C) + \int_{\text{inside}(C)} [I(x) - c1]^2 dx + \int_{\text{outside}(C)} [I(x) - c2]^2 dx \quad (4)$$

where C is the curve to be evolved, $I(x)$ is input image, c_1 and c_2 represent interior and exterior mean intensities and λ is regularization weight controlling the smoothness of contour. Level set formulation [12-13] expressed in Equation (5) is obtained by replacing unknown curve C with level set function ϕ (often signed distance function is used for quick differentiation). The interior and exterior points of curve are obtained using Heaviside approximation (H) whereas curve itself is identified by using derivative of Heaviside function termed as Dirac delta (δ).

$$F(c_1, c_2, \phi) = \lambda \delta(\phi(x)) \text{smooth}(c) + \int_{\text{int}(C)} [I(x) - c_1]^2 H(\phi(x)) dx + \int_{\text{ext}(C)} [I(x) - c_2]^2 (1 - H(\phi(x))) dx \quad (5)$$

Energy optimization problem of Equation (5) is solved by a series of differential operations on Euler-Lagrange formulation as proposed in original work of Chan-Vese. Using gradient descent method optimal change in level set function (ϕ) can be calculated using Equation (6). For complete mathematical formulation, readers are referred to [4].

$$\frac{\partial \phi}{\partial t}(x) = \partial \phi(x) \int_{\Omega_y} \partial \phi(y) ((I(y) - c_1)^2 - (I(y) - c_2)^2) dy + \lambda \delta \phi(x) \text{div} \left(\frac{\nabla \phi(x)}{|\nabla \phi(x)|} \right) \quad (6)$$

Due to the inherent problem of intensity inhomogeneity in medical images, we employed the localization model of Lankton and Tannenbaum [7] by using ball kernel of radius 5 pixels. This mask ensures to use constrained neighborhood in energy computation for moving curve as shown in Fig. 1(a-b). Mathematical presentation for kernel selection is defined in Equation (7).

$$B(x, y) = \begin{cases} 1, & \|x - y\| < r \\ 0, & \text{Otherwise} \end{cases} \quad (7)$$

Mean intensity inside and outside the contour in localized neighborhood is computed by applying ball mask and Heaviside function as follows:

$$\begin{aligned} c_1(\phi) &= \frac{\int_{\Omega_y} B(x, y) I(y) H(\phi(y)) dy}{\int_{\Omega_y} B(x, y) H(\phi(y)) dy} \\ c_2(\phi) &= \frac{\int_{\Omega_y} B(x, y) I(y) (1 - H(\phi(y))) dy}{\int_{\Omega_y} B(x, y) (1 - H(\phi(y))) dy} \end{aligned} \quad (8)$$

Final curve evolution equation using localized Chan-Vese energy model can be expressed by Equation (9) where $I(y)$ represents localized image selected by mask.

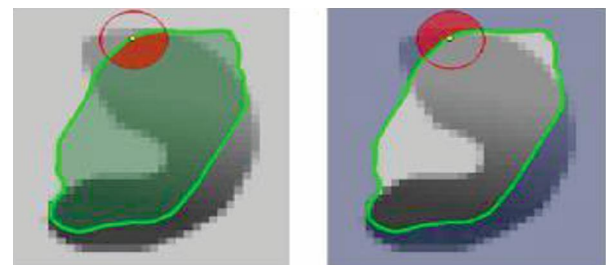
$$\frac{\partial \phi}{\partial t}(x) = \partial \phi(x) \int_{\Omega_y} B(x, y) \partial \phi(y) ((I(y) - c_1)^2 - (I(y) - c_2)^2) dy + \lambda \delta \phi(x) \text{div} \left(\frac{\nabla \phi(x)}{|\nabla \phi(x)|} \right) \quad (9)$$

By discarding the regularization term in Equation (9), localized curve driving force regulating the evolution can be written as Equation (10):

$$F_{total} = \delta \phi(x) \int_{\Omega_y} B(x, y) ((I(y) - c_1)^2 + (I(y) - c_2)^2) dy \quad (10)$$

3.2 Modeling Global Energy

In contrast to Wang and Liatsis [9], where the global model of image was presented in terms of CDF based labelling function; we propose global label based on intensity continuity information. Normalized gradient of the image well defines the global behavior of image in terms of inter-object boundaries, which can be used to improve region based evolution. Strong edges can hold the moving curve to avoid segmentation leakage in



(a) SHADED PORTION IS INTERIOR (b) SHADED PORTION IS EXTE

FIG. 1. LOCALIZATION KERNEL FOR CURVE POINTS TO YIELD LOCAL INTERIOR/EXTERIOR OF CURVERIOR

ambiguous regions where localized statistics gets more chance to push the contour to detect accurate boundaries. Mathematically the image continuity information can be defined as:

$$G(x, y) = \frac{\nabla I(x, y)}{(|\nabla I(x, y)|)} \quad (11)$$

Consequently, the label image representing global behavior is used to compute global force component in bass based constraint region as follows:

$$F_{global} = \int_{\Omega_y} B(x, y)G(y).dy \quad (12)$$

Finally, two components are combined to compute composite force metric responsible for curve evolution in our method as follows:

$$F_{total} = (F_{local}) + b(F_{global}) \quad (13)$$

Substituting the local curve driving force by composite force metric, Equation (13) can be rewritten as Equation (14) which defines the curve deformation force used in this work.

$$F_{total} = \partial \phi(x) \int_{\Omega_y} B(x, y) \left((I(y) - c1)^2 + (I(y) - c2)^2 \right) dy + B \int_{\Omega_y} B(x, y) G(x, y) dy \quad (14)$$

4. RESULTS

In this section we present segmentation results for proposed method on both synthetic and real CT (Computed Tomography) data. It is important to mention that the clinical data has been obtained from a public database names as ‘‘Coronary Artery Evaluation Framework-Challenge’’. This database provides a set of 18 CTA (Computed Tomography Angiography) volumes in context of the coronary segmentation, along with the expert based manual ground truth. In addition, we obtain

CTA data from our clinical partners at St. Thomas & Guys Hospital, London. Accordingly, Fig. 2 shows a synthetic image containing two objects separated by weak boundary. The underlying assumption of homogenous background is well satisfied for this image, which leads to lead to a bimodal histogram; hence, the Yin model works well for this image. However, if the constant background assumption is violated, then this method fails to detect the object boundaries as illustrated in figure below. In contrast, simple localized region based method of Lankton fails to appropriately distinguish the objects due to a very minute intensity deference among two objects. It is important to mention that this small intensity difference leads to over-segmentation, i.e. the evolving contour often captures the boundary of other objects. In this context, the proposed model efficiently segments the object using composite energy. In addition, sensitivity to the initialization mask is also evaluated for three methods by providing different initializations (top versus bottom row). It can be observed from the figure that in contrast to two conventional methods, the proposed model shows a consistent performance in terms of desired segmentation. This is an impressive aspect of the proposed method, as the performance of current segmentation methods remains subjective to initialization.

Fig. 3 presents an image with multiple objects, in which the background is suffering through intensity shift. It is interesting to emphasize that intensity shift in background leads to incorrect labelling in CDF based yin method resulting in degraded segmentation. Similarly localized intensity based decision results in over segmentation due to local optima points, whereas the proposed model successfully detects object boundaries against different initializations based on appropriate weight selection of global force contribution.

Figs. 4-5 simulate a vascular object in noisy medical image suffering from intensity inhomogeneity. At certain points it is evident that weak edges are prone to segmentation leakage in the conventional segmentation methods. This complex behavior makes segmentation non-trivial for single energy metric as Fig. 4(a) shows significant leakage for localization method; whereas the proposed method employing additional information of global outlines detects accurate boundaries against different initializations as shown in Fig. 4(c). Yin's hybrid method mistakenly labels some of the background pixels as part of object due to severe intensity shift, resulting in

inaccurate segmentation as evident in Fig. 4(b). Similarly, Fig. 5 shows resultant segmentations for three methods against two different initializations. The proposed model shows comparatively better performance than others due to additional information employed in curve evolution process.

To demonstrate the effectiveness of the proposed method on real imaging modalities, experimentation was also performed for real CT data. In this test we investigated two CTA volumes, one coming from our clinical partners at St. Thomas & Guys hospital, London,

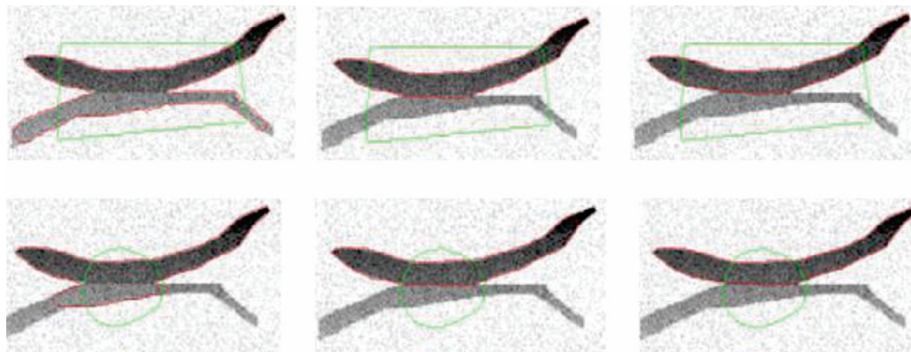


FIG. 2. SEGMENTATION EFFICIENCY OF THREE METHODS AGAINST TWO DIFFERENT INITIALIZATIONS ON SYNTHETIC IMAGE (LEFT) LOCALIZATION METHOD (MIDDLE) YIN'S METHOD (RIGHT) PROPOSED METHOD, GREEN IS INITIALIZATION AND RED IS FINAL SEGMENTATION

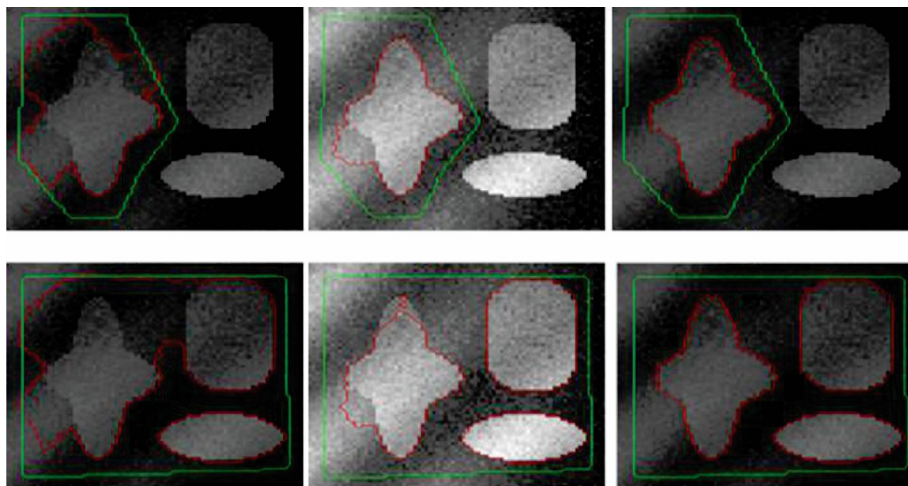


FIG. 3. SEGMENTATION EFFICIENCY OF THREE METHODS AGAINST TWO DIFFERENT INITIALIZATIONS ON SYNTHETIC MULTI-OBJECT IMAGE (LEFT) LOCALIZATION METHOD (MIDDLE) YIN'S METHOD (RIGHT) PROPOSED METHOD, GREEN IS INITIALIZATION AND RED IS FINAL SEGMENTATION

and second from the Rotterdam public database. Once 3D coronary tree has been segmented from the CTA image, we performed skeletonization to extract the corresponding medial axis. Subsequently, the medial axis was employed using CPR (Curve Planar Reformation) technique for extraction of 2D image from 3D CTA data as shown in Figs. 6-7. It is evident from figure that localization method proposed by Lankton fails to detect complete artery in certain cases and leads to leakage at ambiguous boundary points. Moreover, it is also notable

that this technique is very sensitive to the initial mask and demands certain prior knowledge for smart initialization as mask perturbations cannot be addressed easily. Comparatively, Yin's method avoids leakage but due to the CDF based nature of the labelling function, it shows preference towards high intensity areas of object and compromise over low intensity pixels of object. Likewise, it also demands prior knowledge for background suppression in processing stage. In contrast, the proposed method is capable to detect true

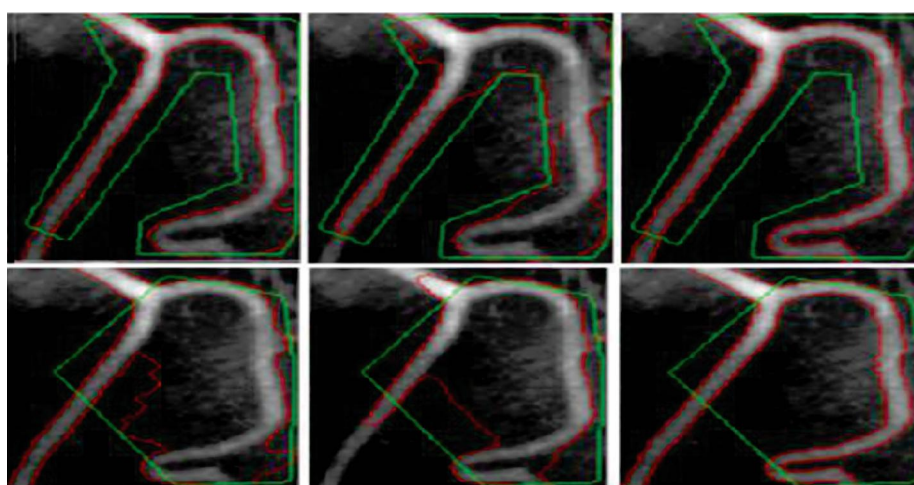


FIG. 4. SEGMENTATION EFFICIENCY OF THREE METHODS AGAINST TWO DIFFERENT INITIALIZATIONS ON SYNTHETIC VASCULAR IMAGE (LEFT) LOCALIZATION METHOD (MIDDLE) YIN'S METHOD (RIGHT) PROPOSED METHOD, GREEN IS INITIALIZATION AND RED IS FINAL SEGMENTATION

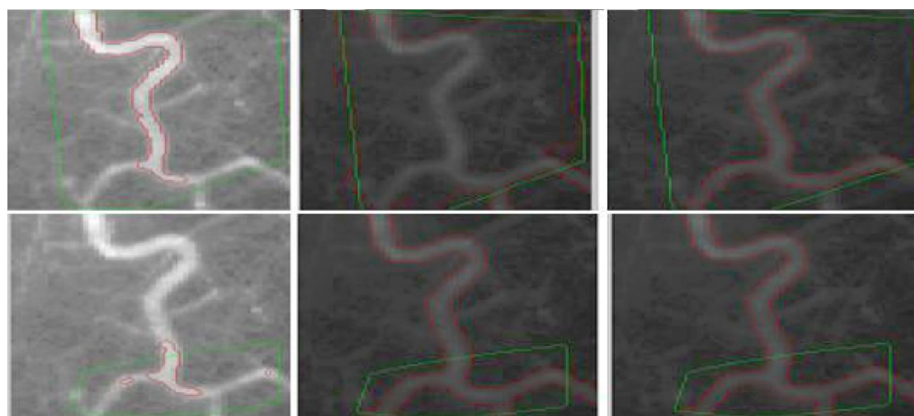


FIG. 5. SEGMENTATION EFFICIENCY OF THREE METHODS AGAINST TWO DIFFERENT INITIALIZATIONS ON SYNTHETIC VASCULAR IMAGE (LEFT) LOCALIZATION METHOD (MIDDLE) YIN'S METHOD (RIGHT) PROPOSED METHOD, GREEN IS INITIALIZATION AND RED IS FINAL SEGMENTATION

boundaries of vessel even for different initializations with adjustment in weight β of global component. It is important to mention that the initialization perturbation can be well handled in the proposed method, β -regulated global component ensures the appropriate

evolution of moving curve towards true boundaries of the object. As the clinical data comes along with the manually annotated reference ground truth, it is easy and realistic to have a qualitative comparison to illustrate the superiority of the proposed method.

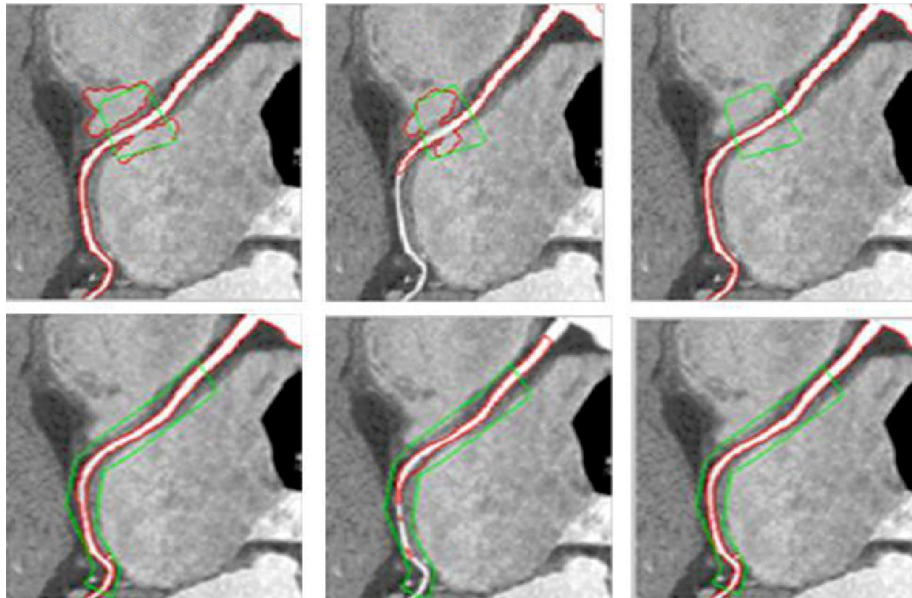


FIG. 6. SEGMENTATION EFFICIENCY OF THREE METHODS AGAINST TWO DIFFERENT INITIALIZATIONS ON CLINICAL CPR IMAGE (LEFT) LOCALIZATION METHOD (MIDDLE) YIN'S METHOD (RIGHT) PROPOSED METHOD, GREEN IS INITIALIZATION AND RED IS FINAL SEGMENTATION

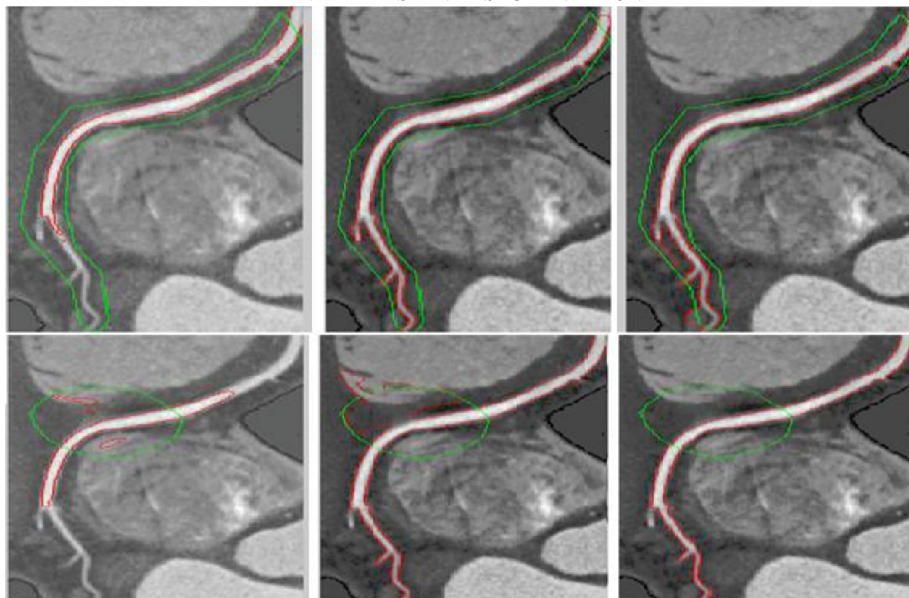


FIG. 7. SEGMENTATION EFFICIENCY OF THREE METHODS AGAINST TWO DIFFERENT INITIALIZATIONS ON CLINICAL CPR IMAGE (LEFT) LOCALIZATION METHOD. (MIDDLE) YIN'S METHOD (RIGHT) PROPOSED METHOD, GREEN IS INITIALIZATION AND RED IS FINAL SEGMENTATION

5. CONCLUSION

An effective yet simple image segmentation method has been proposed in this work that employs composite image force for optimal segmentation. In recent years, hybrid energy based curve evolution has been proposed, the curve evolution can be regulated by combining intensity statistics with posterior-based edge image; however, it increases the computational complexity as pixel-wise posterior computation in an intensive processing task. In contrast, suggest two individual segmentation using different energy models. The limitation of this method is two-fold segmentation and appropriate combinations for effective delineation. In our proposed model, the local region based intensity statistics addresses conventional inhomogeneity problem; whereas, the global component of image pushes the contour rapidly towards object. Accordingly, it is ensured that the contour does not get stuck in local optima points. Incorporation of this additional information in curve evolution process makes segmentation resistant to initialization as perturbations in initial mask are addressed by adjusting the weight of global contribution. A possible limitation of this work includes the optimal selection for global weight i.e. β . It has been observed that a very high value of β pushes the moving contour and weak boundaries are suppressed, whereas a very small value leads to local energy based segmentation results. The future work aims to compute the optimal value for β using regression, and to extend this work for 3D segmentation of coronary arteries in CTA volume which is part of an ongoing project in our centre.

ACKNOWLEDGEMENT

Authors acknowledge the support of our clinical partners for provision of real time CTA data. In addition, we are thankful to the editor and reviewers in helping us to improve the quality of this manuscript.

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