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Fuzzy Membership Function Based Localization of Spinal Cord in Computer Tomographic Images

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Abstract: - **Automatic segmentation of bone in computed tomography (CT) images is critical for the implementation of computer-assisted diagnosis which has increasing potential in the evaluation of various spine disorders. Of the many techniques available for delineating the region of interest (ROI), active contour methods (ACM) are well-established techniques that are used to segment medical images. The project presents a methodology for automatic contour initialization in ACM and demonstrates the applicability of the method for medical image segmentation from spinal CT images. Initially, a set of feature markers from the image is extracted to construct an initial contour for the ACM. A fuzzified corner metric, based on image intensity, is proposed to identify the feature markers to be closed by the contour. A concave hull based on α shape is constructed using these fuzzy corners to give the initial contour. The results show the method's robust performance in the presence of different noise levels.**

I. INTRODUCTION

The spine forms an important support structure in thehuman body, playing a central role in the human biochemical system. Many factors, such as spine fractures caused byspine diseases, accidental injuries, herniations, and degenerativediseases like osteoporosis, vertebral neoplasm or scoliosiscan seriously affect this system causing, in most cases, back pain. Back pain has a great impact on quality of life,being an important public health problem in industrialized countries and a common cause of disability, activitylimitation, work absenteeism, financial burden and a frequentreason for medical consultation. In addition, the organmost commonly affected by metastatic cancer is the skeletonand the spine where it causes the highest morbidity, being thevertebral bodies the most common site for metastaticinvolvement in the spine (80%)
Devising an automatic method for detection and segmentation in medical images poses varied challenges. Formulating an effective delineation technique for extracting the region of interest (ROI), in complex structures like the spine, is an arduous process. In order to assist in this process, various semi-automatic techniques are prevalent for segmenting the object of interest, including methods based on a global threshold; however, a global threshold selection is not straightforward. Use of a single hard threshold is considered a source of segmentation errors. Additionally, the pixels assigned to a single class need not necessarily form a coherent region since spatial locations are ignored. Histograms are drawn, and the valleys are identified as potentialrate, necessitating the development of robust automatic segmentation methods. ACMs are a viable option for the automatic segmentation of medical images if robust computational methods for contour initialization are made available. The fully automatic segmentation of spinal CT images is presented here. For the spine presents an algorithm which utilizes an edge detection function and region detection function to extract lumbar vertebrae for identifying disc herniation. This method is initialized with an Otsu threshold. The level set is formulated in terms of intensities by adding a weighted kernel to each pixel, where the edge stopping function is defined in terms of Euler Lagrange coefficients. Wu and Lin were able to identify dominant features in cervical vertebrae with a similar thresholdbased initialization approach. To overcome the inherent drawbacks of thresholding, an adaptive 3D region growing method is devised in. While it calls for seed placement in the canal, a level-set is allowed to evolve followed by a voxel-based delineation. Certain morphological operations are allowed to enhance the process. A three step algorithm is adopting Statistical Shape Models (SSM) that includes a seed placement, initial labeling and final optimization. This method is designed to handle complex geometry of all processes and variability between the individuals. An initialization-free active contour method for generic images that use radial basis function at its core level set. Its response on images with noise and artifacts are yet to be explored. The deterministic computational methods used in order to segment an image, deteriorate in the presence of noise. However, employing soft computing techniques like fuzzy logic can improve the performance. Fuzzy rule based systems are built upon multiple combinations of thresholding.

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The present work is a novel technique that focuses on development of automatic contour initialization with fuzzy feature points while using the conventional ACM. Originality of the work manifests in the germination of initial contour which is directly associated with image features rather than a template or manual labor. A fuzzified corner metric based on image intensity is proposed to identify the feature markers which are enclosed by the contour. A concave shape approximating the boundary of these fuzzy corner points is obtained using α hull to provide initial contour for the ACM. Most of the existing methods are manual and face discrepancies in segmenting a stack of slices, while the proposed method will exploit the dearth in automation of such processes. The proposed method which is evaluated against conventional feature detectors and other generic initialization techniques, is found to perform robustly even in the presence of noise.

II - RELATED WORK

In [1], Shawn Lankton, et al., propose a natural framework that allows any region-based segmentation energy to be re-formulated in a local way. We consider local rather than global image statistics and evolve a contour based on local information. Localized contours are capable of segmenting objects with heterogeneous feature profiles that would be difficult to capture correctly using a standard global method. Juying Huang, et al.,[2] proposed model can efficiently segment images with intensity inhomogeneity and blurry or discontinuous boundaries. To reduce the dependency on manual initialization in many active contour models and for an automatic segmentation, a simple initialization method for the level set function is built, which utilizes the Otsu threshold.

Xun Wang b, et al.,[3] proposed the segmentation task that is required for biomedical applications is usually not simple. Critical issues for any practical application of DCMs include complex procedures, multiple parameter selection, and sensitive initial contour location. Guidance on the usage of these methods will be helpful for users, especially those unfamiliar with DCMs, to select suitable approaches in different conditions. K. Lekadir, et al., [5] this approach does not take into account the relative position, orientations and shapes among the parts of an articulated object, which may result in unrealistic geometries, such as with object overlaps. In this article, we propose a new Statistical Model, the Statistical Interspace Model (SIM), which provides information about the interaction of all the individual structures by modeling the interspace between them. The SIM is described using relative position vectors between pair of points that belong to different objects that are facing each other.

F. Frangi, et al., [6] proposed technique is specifically developed with the aim to handle the complex geometry of the processes and the large variability between individuals. The key technical novelty in this work is the introduction of a part-based statistical decomposition of the vertebrae, such that the complexity of the subparts is effectively reduced, and model specificity is increased. Subsequently, in order to maintain the statistical and anatomic coherence of the ensemble, conditional models are used to model the statistical inter-relationships between the different subparts.

III - PROPOSED SYSTEM

This project proposes automatic contour initialization for ACM based medical image segmentation. A set of feature markers from the image is extracted to construct an initial contour for the ACM. A fuzzified corner metric based on image intensity is proposed to identify the feature markers that are enclosed by the contour. A concave hull based on α shape, is constructed using these fuzzy corners yielding the initial contour which evolves due to the image forces. The segmented output is validated using similarity metrics computed from the ground truth segmentation performed by experienced radiologist.

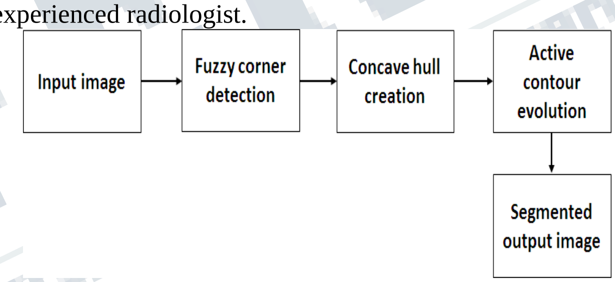

Fig 1.Proposed Block

A. Active contour methods

$$E = \int_0^1 E_{int}\big(V(s)\big) + E_{irng}\big(V(S)\big) + E_{ext}\big(V(S)\big)ds$$

Where v(s) = (x(s), y(s)) represents the parameters of snake, Eint = (α(s) [v(s)] 2 +β(s) [v(s)] 2/=2 with α and β contributing for elasticity and rigidity components of internal energy, Eimg accounts for image force and Eext provides external constraint force that is modeled depending on the application. External energy drives the contour using image data while the internal energy stabilizes its shape based on general smoothness constraints. Level sets are special classes of these contours in which one traces the evolution of curve at the zero level. The method embeds an interface in a higher dimensional function ϕ (signed distance function) as a level set ϕ=0. The equation that governs evolution of level set function ϕ (t), is, $\frac{\partial \varphi}{\partial t} + F|\nabla\varphi| = 0$ where F represents speed function. The CV model which controls evolution

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without edges, and it is described in the energy functional given in Eq. (2). By incorporating the external image forces and minimizing it, the corresponding variational level set formulation can be obtained solving the Euler Lagrange equation.

$$E^{CV} = \lambda_1 \int_{inside(C)} |I(x) - c_1|^2 dx + \lambda_2 \int_{outside(C)} |I(x) - c_2|^2 dx, x\epsilon\Omega$$

The ACM methodology is adapted for this work owing to its added advantages. It enhances the level set framework bypassing the calculation of signed distance function. In this method, a special region based function forces the level sets to be binary and a Gaussian function is used for further regularization. A signed pressure force is formulated as a region based function that effectively stops at blurred edges given by:

$$spf(I(x)) = \frac{I(x) - \frac{c_1 + c_2}{2}}{\max(|I(x) - \frac{c_1 + c_2}{2}|)},$$

Where c1 and c2 are computed using the regular Heaviside function. The final level set formulation is given as,

$$\frac{\partial\varphi}{\partial t} = spf(I(x))\left(div\left(\frac{\nabla\varphi}{|\nabla\varphi|}\right) + \alpha\right) + \nabla spf(I(x)).\nabla\varphi$$

Where α is a constant velocity term added to increase the speed of propagation of contour. Combining the merits of traditional approaches namely the CV and GAC models, this method stops at weak boundaries and edges. It provides selective local or global segmentation upon determining a suitable binary function. However, the user has to initialize and provide a tuning parameter for each input image. Taking these aspects into account, this paper proposes a technique for automatic initialization of contours based on fuzzy corners and α hull.

B - Fuzzy corner detection

Corners are feature points in an image that are identified by presence of large variation in intensity around a pixel in all directions. One of the well-known corner detectors is Harris corner and edge detection method. The corners are detected using the Eigen value distribution obtained from a corner response metric. The corner metric R(x) for each pixel with intensity x(u,v) is defined by the Eq. (5).

$$\boldsymbol{R}(x) = I_u^2 * I_v^2 - (I_u I_v)^2 - k(I_u^2 + I_v^2)^2$$

Where:Iu/v – intensity gradient along u / v; k-sensitivity factor. In order to identify local maxima of this cornerness, a pixel neighborhood of 8 pixels is taken and a non maxima suppression is exerted to yield the suppressed cornerness Cr(x). This involves extraction of a singular point among the connected components that is likely to have the same intensity and belong to the same local maxima. By shrinking the pixels linked to each other in the absence of a hole or by placing them in the mid stance between a hole and a boundary, multiple copies of maxima are removed. This results in pixels with maximum corner strength from its neighboring counterparts. These pixels are sorted in ascending order of their cornerness strength and a certain threshold in their numbers is used to extract the corners in the Harris scheme. In case of medical images, like CT, apart from bone regions that have high intensity, the surrounding muscle regions are also captured with varied intensity scale.

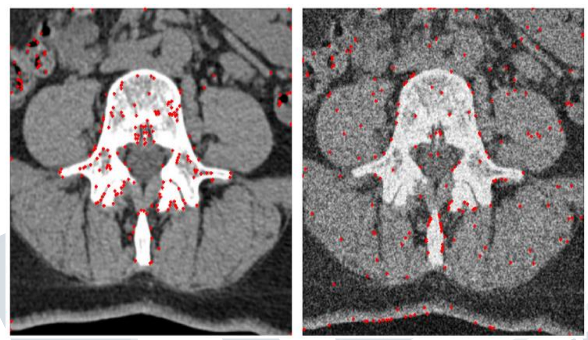

Fig. 2. Harris corners detected for an axial spine CT image (a) normal image (b) noisy image.

An example for an axial CT slice of spine is shown in Fig. 2. The conventional Harris corner detects corners in the ROI along with stray corners in other regions. If the Harris corners are used to construct the contour for ACM, the efficiency of contour evolution will be compromised and in some cases, the contour may deviate from the intended boundary of ROI. The corner detection is further effected in the presence of noise as shown in Fig. 2b. To identify the potential corners lying in the ROI, it is imperative to check if the feature is a true candidate, for which, classification techniques can be adopted. In order to identify feature points of interest robustly even in the presence of noise, we propose a fuzzy corner metric that uses a fuzzified intensity mask on the corner metric obtained from conventional Harris scheme. Fuzzy logic theory helps in capturing uncertainties in an image and provides a formal way of exploring it as perceived by humans. An image can be considered a as a fuzzy set whose gray level constitutes the subset. Let X be the fuzzy set consisting of image intensities x and is characterized by a continuum grade membership function μ(x) whose value ranges between 0 to 1. Specifically, an S type membership function is employed for fuzzifying the intensities of input images in this work. This type of membership function is opted to give higher weightage to pixels with higher intensities and thus segment bony

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structures from CT images. The functional definition of fuzzy membership function is given in Eq. (6).

$$\boldsymbol{S}(x;a,b)=\begin{cases}0, & x\le a\\ 2\left(\frac{x-a}{b-a}\right)^2, & a\le x\le \frac{a+b}{2}\\ 1-2\left(\frac{x-a}{b-a}\right)^2, & \frac{a+b}{2}\le x\le b\\ 1, & x\ge b\end{cases}$$

Where x=input image intensity, a=foot point, b=peak point and S (x) =fuzzified intensity. Upon fuzzifying the image domain, a threshold is set for extracting the pixels that are likely to contain corner features. The fuzzified threshold intensity t(x) is given by Eq. (7).

$$\boldsymbol{t}(x)=\begin{cases}S(x),\&S(x)>th\\ 0,S(\&x)\le th\end{cases}$$

Where t(x) =fuzzy thresholded intensity; th =threshold whose value is set to extract top 90% of image features. This function is used as a mask for identifying significant corner points from the derived corner strength matrix. The weighted combination of suppressed corner strength with the fuzzy thresholded input image (as given by Eq. (8)) gives fuzzy corners for the image.

$$\boldsymbol{C}(x)=\boldsymbol{t}(x)*\boldsymbol{C_r}(x)$$

The fuzzified corners eliminate corners that are formed as a result of cavity (darker spots inside a predominant high intensity region), spurious edges, noise and artifacts. For the axial image displayed in Fig. 2(a), the fuzzified corner metric is evaluated which is used to detect fuzzy corners as shown in Fig. 3. It is observed that the fuzzy corner points estimate the ROI closer than the corners detected using Harris scheme.

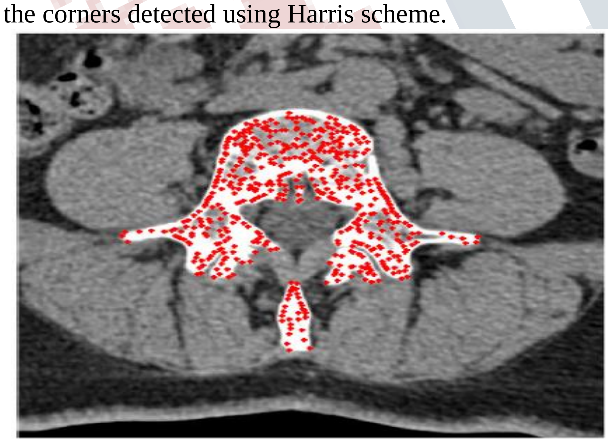

Fig. 3. Fuzzy corners detected in an axial spine image.

(i) Contour initialization using α hull

Once the feature points are identified, the next step is to wrap them up in a close – knit curve which gives the initial contour for the ACM evolution. Since these feature points are located on edges and corners, they can attribute to shape the initial contour. One of the simplest choices would be to form a convex hull. A set S in Euclidean space is said to be convex if every straight-line segment having its two end points in S lies entirely in S. The smallest convex set that contains the entire point set is its convex hull which is described by the convex combination of finite subset of points in C, as given in Eq. (9).

$$H(C)=\sum_{i=1}^{n}\theta_i c_i, c_i\in C \text{ and } \sum\theta_i=1 \text{ for } i=1,2,\ldots.n$$

These hulls can also be used as a metric for evaluation of boundaries in medical images. While a convex hull is good for bounding a region of points, it does not describe the shape of an object. Concave hulls perform much better for describing the region occupied by a point set. The mathematical background of a commonly used algorithm that uses concave hull based on α shapes is found. An α shape is generated by point pairs with a parameter α, controlling the desired level of details. It is a sub graph of Delaunay triangulation of points considering that two points are connected if there is an empty ball of radius alpha touching them. When α tends to infinity, the α hull approaches the convex hull of a given point set

C - ALGORITHM

A stepwise description of the complete method is given below,

1. Corner detection

Detect the traditional Harris corners in parent image using cornerness measure R(x)
Modify the corner metric using the fuzzy approach
Output the fuzzy corners C(x)

2. Construction of concave hull

Construct the Voronoi diagram and Delaunay triangulation of C (x)
Decide the α parameter
Determine the α-extremes of C(x)
Determine the α-neighbors of C(x)
Output the α-shape of the provided saliency points

3. Contour evolution

Initialize the level set function

$$\varphi(x,t=0)=\begin{cases}-1x\in interior of \alpha hull\\ 0x\in boundary of \alpha hull\\ 1x\in exterior of \alpha hull\end{cases}$$

Compute c1 and c2
Evolve the level set equation given in Eq. (4)
Add regularization parameter with a Gaussian kernel if necessary
Check for convergence else Repeat

IV - SIMULATION RESULTS

The proposed work is simulated with the UCI dataset which are received in DICOM format with 256X256 dimensions. The following figure shows the sample dataset image.

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Figure 3 sample dataset image

Figure 4 Median filtered image

The fuzzy corner points are displayed on the following figure where the tumor region is having more number of corner pixels and the fuzzy corner points are plotted on the original image which is also show along with the same figure 5

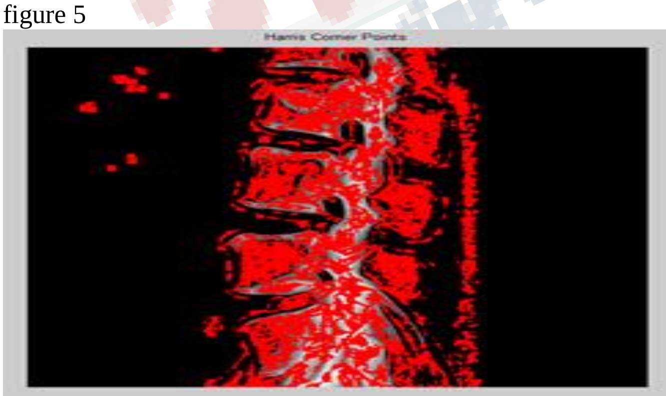

Figure 5 corner image

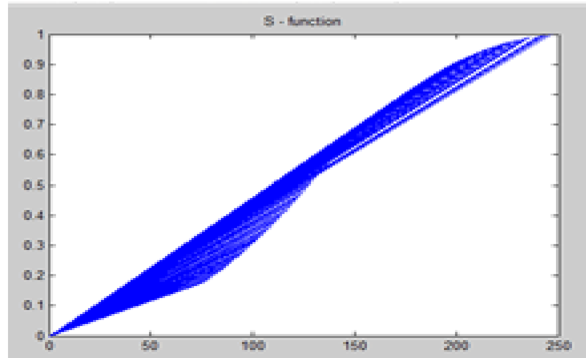

Figure 6 s – membership function

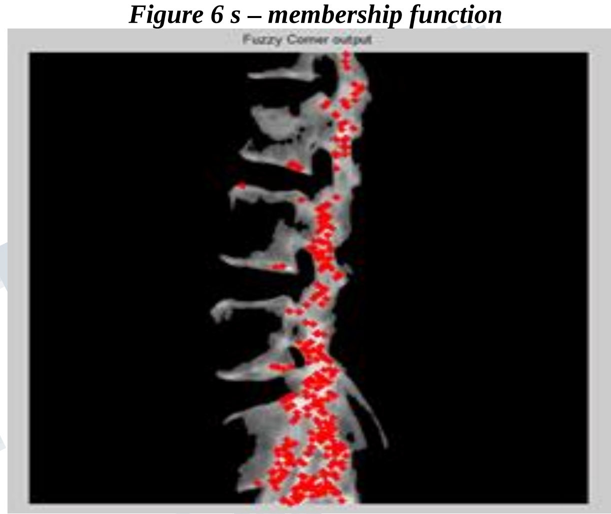

Figure 7 fuzzy corner images

The alpha hull based active contour segmentation is applied for the corner pixels where the contour represents the brain tor area. The below figure shows the alpha hull contour obtained for the test image shown in these sequence of discussion.

Figure 8 Alpha hull based contour

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The active contour segmentation is applied on the predicted contour region and the result will be obtained in both gray and binary scales for further analysis. He following figure shows both the binary and grayscale images obtained

Figure 9 active contour image

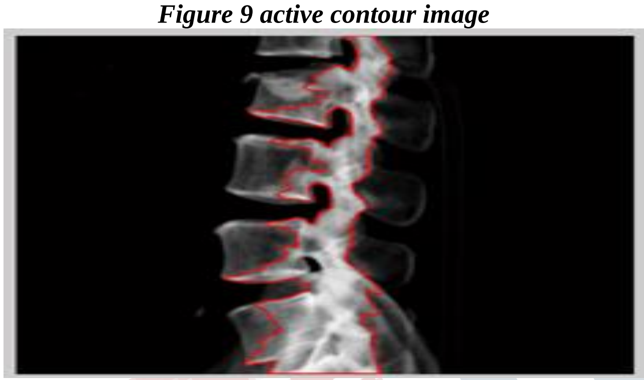


Figure 10 final labeled spin image

(I)Performance Evaluation

Performance measure procedure was done by comparing the segmentation results to the reference image. There are four values resulted from the validation procedure, true positive (TP), false positive (FP), true negative (TN) and false negative (FN). True positives is a number of pixels correctly detected as vessel pixels, false positive is a number of pixels incorrectly flagged, true negatives is a number of pixels correctly detected as non-vessel and false negative (FN) is a number of pixels incorrectly flagged as non-vessels.

Table 4.2 Performance Parameters

	Vessels	Non - vessels
Detected	True positive (TP)	False positive (FP)
Not detected	False Negative (FN)	True Negative (TN)

For evaluation purpose, all the parameters are determined for each image in the data set. Sensitivity, Specificity and Predictivity are used as accuracy measures.

(a)Sensitivity

It is the probability that a test result will be positive when the selected pixel is vessel. It is defined as the ratio between True positive (TP) and addition of True positive (TP) and False negative (FN).

$$Sensitivity = \frac{TP}{(TP + FN)}$$

(b) Specificity

It is the probability that a test result will be negative when the selected pixel is non-vessel. It is defined as the ratio between True negative (TN) and addition of False positive (FP) and True negative (TN).

$$Specificity = \frac{TN}{(FP + TN)}$$

(c) Predictivity

It is the probability that the vessel is present when the detected while tracing. It is defined as the ratio between True positive (TP) and addition of True positive (TP) and False positive (FP).

$$Predictivity = \frac{TP}{(TP + FP)}$$

(II) Performance Results of vessel Segmentation

The above parameters are measured for the six sample images and tabulated in Table 4.2

Table 4.2 Parameter results

Image name	Sensitivity	Specificity	Predictivity
Sample 1	0.9796	0.5000	0.9796
Sample 2	0.9524	0.6667	0.9756

(III) Comparison of Results

The evaluated results are compared with the manual segmented results. The samples are segmented by manual segmentation and the performance of proposed segmentation method is compared with the latter method. The graphical comparisons are shown in Figure 4.13 to Figure 4.14

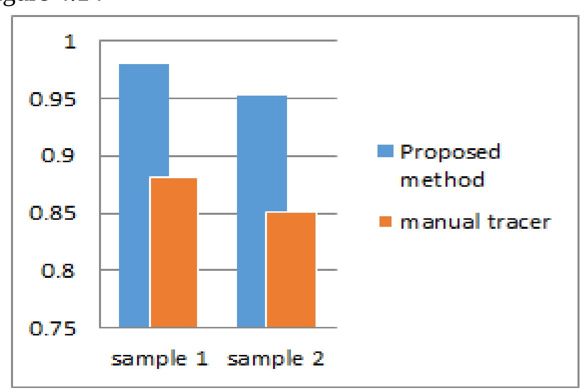
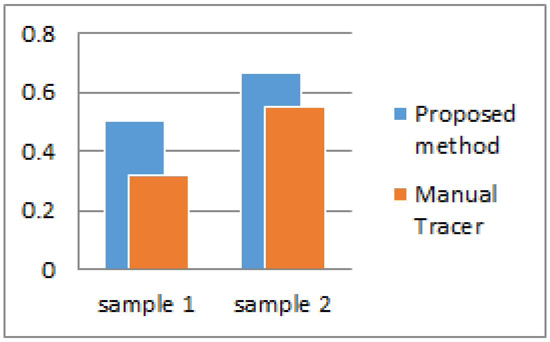


Figure 4.13 Sensitivity comparison



Specificity comparison

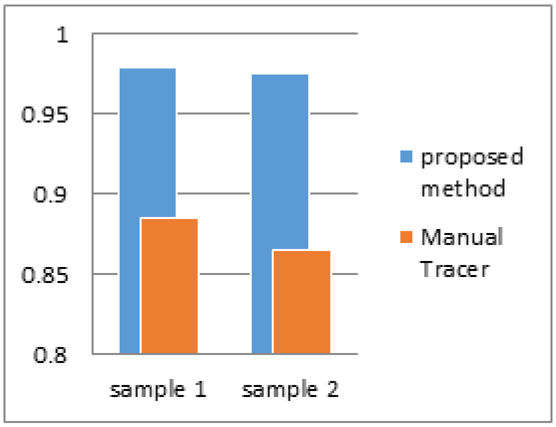


Figure 4.15 Predictivity comparison

The overall parameters for both Graph tracer and Manual Tracer are plotted in Figure 4.16

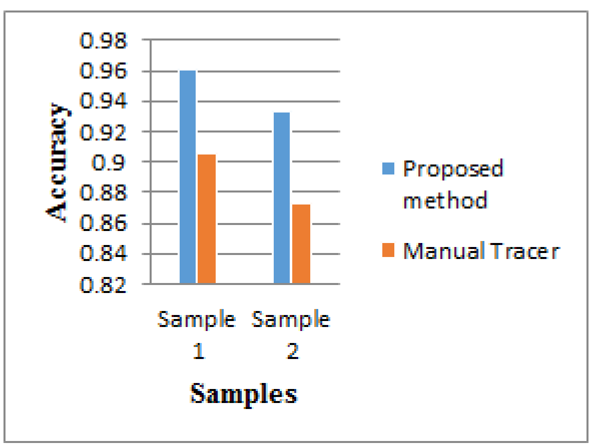


Figure 4.16 Performance comparison

V - CONCLUSION

Segmenting regions from medical images is an involved process for various reasons. Deformable contours provide an almost accurate dissection of ROI from back ground owing to their ability to constrict or expand upon external constraints. There liability of such segmentation can only be guaranteed if the initial contour is close enough to the interest segment. To ensure good results, manual setting has so far been the only viable option which increases the fatigue of clinical users. To facilitate a smooth and less intensive segmentation, a novel method of automatic contour initialization for ACM is presented in this study. The proposed method uses a fuzzified corner metric based on image intensity to identify the feature markers enclosed by the contour. A concave shape approximating the boundary of these fuzzy corner points is obtained using α hull to give the initial contour for the ACM. The proposed method is evaluated against conventional feature detectors namely the Harris corner and SUSAN corner detection using the similarity indices (DC and HD). It can be inferred from the mean and SD values of DC (0.92116, 0.06323) and HD (5.7619, 2.3606) that the proposed method out- performs other schemes in terms of segmentation accuracy. The additional computational cost is one order less than the cost of ACM evolution. The proposed technique is proven to perform robustly even in the presence of noise.

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