An Improved Method for Medical Image Segmentation using Parametric Deformable Model with Statistical Approach

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Abstract - In the field of medical informatics image analysis is a challenging responsibility. Automated image segmentation is mostly used for automated extraction image features or the region boundary features which are considered as the major components in understanding image content for searching and mining. But in particular, medical images are often corrupted as such a challenging problem is to segment regions with boundary insufficiencies, i.e., missing edges and/or lack of texture contrast between regions of interest (ROIs) and background due to noise and sampling artifacts causing considerable difficulties for classical segmentation techniques like edge detection and thresholding. These techniques either fail completely or require some kind of post-processing step to remove invalid object boundaries in the segmentation results. To address these difficulties, deformable models have been extensively studied and widely used in medical image segmentation. In this paper a hybridized process model based on parametric deformable i.e. active contour based method along with statistical analysis techniques using PCA+FLDA is proposed for image segmentation with promising results.

Keywords:- *Image Segmentation, medical Images, Parametric Deformable Models, statistical features, Level Set, PCA,LDA,FLDA etc.*

I. INTRODUCTION

Diagnostic imaging is an invaluable tool in medicine and imaging and computer vision technology have increased their scope in this field. Image segmentation is an important and necessary step during the image analysis or preprocessing phase. However, in the real time scenario due to the imperfection of the image acquisition process, intensity inhomogeneity (or bias field) is often seen in many real-world images, especially in medical images [4, 5].

For proper analysis and diagnosis in medical field it is very important to transform acquired raw images into a numerically symbolic form for better representation, evaluation, and/or content based search and mining. One of the most important step in this transformation is the segmentation to obtain the target location and structures that could be based on given homogeneity criteria, the image partitioning into regions where medical images are usually the target anatomic regions i.e. foreground and their surroundings also called background. After this segmentation, the exact shape and appearance features of the targets can be calculated, and, based on the application; they can be used for clinical evaluation, pattern analysis, and/or knowledge discovery. A challenging problem is to segment regions with boundary insufficiencies, i.e., missing edges and/or lack of texture contrast between regions of interest (ROIs) and background.

As discussed in [6] the intensity inhomogeneity in magnetic resonance (MR) images usually manifests itself as a smooth intensity variation across the image. Thus the resultant intensities of the same tissue vary with the locations of the tissue within the image. This can cause serious misclassifications when intensity-based segmentation algorithms are used. Therefore, intensity inhomogeneity has been challenging difficulty in image segmentation.

Deformable models are curves or surfaces, for segmentation in the image domain, or hyper-surfaces, for the segmentation of higher dimensional image data, such as stacks of images, which deform under the influence of internal and external forces to delineate object boundary. The internal forces are defined such that they preserve the shape smoothness of the model, while the external forces are defined by the image features to drive the model toward the desired position/ configuration, i.e., to the desired region boundaries. Usually, the core model definition is independent from the features used in the external force terms; in most cases, the image features are application-related, i.e., their choice depends on the image modality. For instance, in ultra-sound images, different regions are determined by region contrast, in terms of the intensity speckle density/distribution, while the edge information, in its definition as the image gradient, is usually too poor to be used. On the other hand, magnetic resonance (MR) and computerized tomography (CT) images have sufficient gradients for edge information to be used in segmentation.

Deformable models are classified into two general approaches, the parametric and the geometric models, depending on how the model is defined in the shape domain.

Intuitively, parametric models, widely known as active contours for the segmentation in the two-dimensional image domain, are curves whose deformations are determined by the displacement of a discrete number of control points along the curve. Apart from active contours, parametric models can be also surfaces, with the control points defining two-dimensional (in the shape domain) deformable grids, for two-dimensional image segmentation, or hyper-surfaces, with the control points defining three-dimensional, intraconnected, clouds of points, for the segmentation of higher-dimensional image data (e.g., image stacks).

The main advantage of parametric models is that they are usually very fast in their convergence, depending on the predetermined number of control points. However, an obvious weakness of these models is that they are topology dependent: a model can only capture a single ROI, and therefore, in images with multiple ROIs, multiple models have to be initialized, one for each ROI.

Ahmed E. et al. (2019) has developed a robust 3-D segmentation technique incorporated with the level sets concept and based on both shape and intensity constraints. This advanced method of segmentation is based on partial differential equation (PDE) is derived to describe the evolution of the level set contours. This PDE does not contain weighting parameters that need to be tuned, which overcomes the drawbacks of other PDE approaches. The shape information is collected from a set of co-aligned manually segmented contours of the training data. A promising statistical approach is used to get the distribution of the intensity gray values. The introduced statistical approach is built by modeling the empirical PDF (normalized histogram of occurrences) for the intensity level distribution with a linear combination of Gaussians (LCG) incorporating both negative and positive components.

Carlos E. et al. (2019) have discussed in their work about the manual image segmentation techniques in which they analyzed that manual method is time-consuming task which is routinely performed in radiotherapy to identify each patient's targets and anatomical structures. The efficacy and safety of the radiotherapy plan requires accurate segmentations as these regions of interest are generally used to optimize and assess the quality of the plan. However, reports have shown that this process can be subject to significant inter- as well as intra observer variability. Furthermore, the quality of the radiotherapy treatment, and subsequent analysis could be subjected to the accuracy of these manual segmentations. Automatic segmentation also known as auto-segmentation mostly targets normal tissues and hence preferable as it would address these challenges. In the analysis they observed that in auto-segmentation techniques there have been clustered into 3-generations of algorithms with multi-atlas based and hybrid techniques (third generation) being considered the state-of-the-art. More recently, however, the field of medical image segmentation has seen accelerated growth driven by advances in computer vision, particularly through the application of deep learning algorithms, suggesting we have entered the fourth generation of auto-segmentation algorithm development. Hence the authors reviewed the traditional (non-deep learning) algorithms particularly relevant for applications in radiotherapy and further drawn a the concepts from deep learning focusing on convolutional neural networks and fully-convolutional networks which are generally used for segmentation tasks. Furthermore, they authors provided a summary of deep learning auto-segmentation radiotherapy applications reported in the literature. Lastly, considerations for clinical deployment commissioning and QA of auto-segmentation software are provided. [2]

As analyzed in the literature the level set methods are considered as a numerical technique and mostly used for tracking interfaces and shapes [11]. Further, In [12,13] found its significance in image segmentation since past decades.

Compared with the classical image segmentation methods such as edge detection, thresholding, and region growing, level set methods have three desirable advantages. First, they can achieve sub-pixel accuracy of object boundaries [14]. Second, they allow incorporation of various prior knowledge, for example, shape and intensity distribution, so as to get more robust segmentation [15,16]. Third, they can provide smooth and closed contours as segmentation results, which are necessary and can be readily used for further applications such as shape analysis and recognition [7,17]. In general, the existing level set methods can be categorized into two classes: edge-based models [7,14, 18–20] and region-based models [7,17, 21–25].

Edge-based models typically use image gradient as an image-based force to attract the contour toward object boundaries. These models have been successfully used for general images with strong object boundaries, but they are generally sensitive to the initial conditions and may suffer from boundary leakage problem for medical images which typically contain weak boundaries. These drawbacks greatly limit their utilities for medical images. Region-based models use a certain region descriptor to guide the motion of the active contour. Therefore they are less sensitive to initial contours and have better performance for images with weak object boundaries. A typical example is the piecewise constant (PC) model proposed in [21]. This model assumes that image intensities are statistically homogeneous in each region and thus always fails to segment images with intensity inhomogeneity. Intensity inhomogeneity can be dealt with by more complicated models than PC model. Tsai et al. [24] and Vese and Chan [25] independently proposed two similar region-based models, widely known as piecewise smooth (PS) models, for segmentation of more general images. The PS models cast image segmentation as a problem of finding an optimal approximation of the original image by a piecewise smooth function. Although the PS models do not assume homogeneity of image intensities and therefore are able to segment images with intensity inhomogeneity to some extent, they are computationally too expensive.

Recently, local intensity information has been incorporated into level set methods to effectively handle intensity inhomogeneity [8, 17, 26-31]. For example, Li et al. [17] defined a region-scalable fitting (RSF) energy in terms of a contour and two fitting functions that locally approximate the image intensities on the two sides of the contours. Based on the multiplicative model of images with intensity inhomogeneity and a derived local intensity clustering property, Li et al. [29] presented a variational level set framework for simultaneous segmentation and bias correction. Similarly, Chen et al.[27] adopted localized K-means-type clustering to define an energy which contains the bias field as a variable, and thus the energy minimization can also implement image segmentation and bias field estimation simultaneously. These models essentially draw upon local intensity means, which enable them to cope with intensity inhomogeneity. However, the local intensity means do not provide enough information for accurate segmentation, especially in the presence of strong noise and intensity inhomogeneity [8].Therefore, more complete statistical characteristics of local intensities recently have to be taken into account. For instance, Rosenhahn et al. [26] used both local intensity means and variances to characterize the local intensity distribution in their proposed level set method. However, the local intensity means and variances are defined empirically in their models.

In this context in Julia K.et.al. [4] have suggested that a model-based image analysis is indispensable in medical image processing. One key aspect of building statistical shape and appearance models is the determination of one-to-one correspondences in the training data set. At the same time, the identification of these correspondences is the most challenging part of such methods. In this work they have developed a a new approach for statistical appearance models without one-to-one correspondences is proposed. A sparse image representation is used to build a model that combines point position and appearance information at the same time. Probabilistic correspondences between the derived multi-dimensional feature vectors are used to omit the need for extensive preprocessing of finding landmarks and correspondences as well as to reduce the dependence of the generated model on the landmark positions. Model generation and model fitting can now be expressed by optimizing a single global criterion derived from a maximum a-posteriori (MAP) approach with respect to model parameters that directly affect both shape and appearance of the considered objects inside the images. During the extensive analysis of statistical approach for medical image segmentation**,** Nandi D.et. al. [5] have done the thorough analysis of Principal component analysis (PCA) technique in medical image segmentation which is a mathematical procedure which uses sophisticated mathematical principles to transform a number of correlated variables into a smaller number of variables called principal components. In PCA, the information contained in a set of data is stored with reduced dimensions based on the integral projection of the dataset onto a subspace generated by a system of orthogonal axes. The reduced dimensions computational content is selected so that the significant data characteristics are identified with little information loss. Such a reduction is an advantage in several fields as for image compression, data representation, etc. It can also be widely used for feature extraction, image fusion, image compression, image segmentation, image registration, de-noising, etc. This paper presents a survey of the applications of PCA in the field of medical image processing. In this study, various medical image application-based PCA results are exhibited to prove its efficiency.

Recent advances in variational formulation, such as [12], provide new possibilities in numerical implementations. However, it is still a great challenge for active contour models to achieve strong invariance to initialization and robust convergence. This is particularly true when the active contour is applied on real image datasets consisting of intensity inhomogeneity and complex geometries. In the presence of artifacts, occlusions or large amount of noise, it is difficult for purely image-based models to extract image objects accurately. In such cases, prior knowledge of shape information can be very useful as it provides a constraint to the deformation of the contour such that the model favors similar shapes represented in the training set. One of the earliest approaches in modeling shape information uses an explicit representation of the shapes.

The paper presents an improved local region-based active contour model for image segmentation, which is robust to noise. A data fitting energy functional is defined in terms of curves and the energy terms which are based on the differences between the local average intensity and the global intensity means. Then the energy is incorporated into a level set variational formulation, from which a curve evolution equation is derived for energy minimization. And then the level set function is regularized by Gaussian filter to keep smooth and eliminate the re-initialization. By using the local statistical information, the proposed model can handle with noisy images. The proposed model is first presented as a two-phase level set formulation and then extended to a multi-phase one. Experimental results show desirable performances of the proposed model for both noisy synthetic and real images, especially with high level noise.

In [35], the training shapes are represented using landmark or control points, and principal component analysis (PCA) is used to model the variability of the training set. The algorithm is based on a parametric point distribution model that uses linear combinations of the eigenvectors to represent variations from the mean shape. The shapes are aligned using an iterative technique called the procrustes analysis [36], such that the shape model is more robust to rigid transformations such as translation, rotation, and scaling. The use of landmark points, however, has a drawback as the accuracy of the shape analysis depends on the quality of the landmarks. In addition, such shape models require the parameterization of the active contours. Recently, various groups [16,37-39] have incorporated shape prior information into the level set framework. In [16], shapes are represented using signed distance functions, and PCA is applied to the training shapes. The prior information is then incorporated into a geodesic active contour [14] to attract the level set function toward similar shapes represented in the shape distribution. The shape model is composed of the mean shape and a weighted sum of the principal modes of variation. In [24], PCA is applied to the space of signed distance functions, and the parameters of the principal eigen modes are optimized efficiently. The signed distance functions are more robust to slight misalignments of the training shapes than parametric contours. However, the space of signed distance function is nonlinear, and the shape representations using linear combination of eigen modes do not, in general, correspond to a signed distance function. In [15], the shape information is imposed onto the contour extracted from the level set function at each iteration. The shape prior, therefore, acts on the contour and has difficulties in modeling topological changes.

II. LEVEL SET METHOD FOR SEGMENTATION

Let I be an image, and g be the edge indicator function defined by,

$$g = \frac{1}{1+|\nabla G_\sigma * I|^2} \qquad (3.1)$$

Then find coefficient of the internal (penalizing) energy term that help contour to outside the object boundary. It defines an external energy for a function Ø(x, y) as below:

$$\varepsilon_{g,\lambda,v}(\phi) = \lambda l_g(\phi) + vA_g(\phi) \qquad (3.2)$$

where λ > 0 and ν are constants, and the terms $l_g(\phi)$ and $A_g(\phi)$ are defined by,

$$l_g(\phi) = \int_\Omega g\delta_g(\phi)|\nabla\phi|dxdy \qquad (3.3)$$

And

$$A_g(\phi) = \int_\Omega gH(-\phi)dxdy \qquad (3.4)$$

This function is known as the level set function. A contour (or level set) *C(t)* is a curve described by a set of points where the function has the same particular value. The zero level set can be written as

$$C(t) = \{(x,y)\in\Omega : \phi(x,y,t) = 0\} \qquad (3.5)$$

where t is a variable that indicates the time step in the evolution of the contour. The zero level contour of the level set function segtnents the image. The contour C is initially approximated.

The level set function is then initialized as the signed Euclidean distance to the contour C. Fig. 5.1.and 5.2. shows the level set function. On the left is the initialization of the level set function and on the right is the level set function that leads to the final segmentation of the image. The initialization has a lot of disconnected pixels on the zero level set, but the level set obtained after applying the segmentation algorithm has only those points that segment the ventricles on its zero level. Here we follow the convention that this level set graph has negative values inside C (pixels belonging to the heart) and positive values outside C.

$$inside(C) = \Omega_1 = \{(x,y)\in\Omega : \phi(x,y,t) < 0\}$$

$$inside(C) = \Omega_1 = \{(x,y)\in\Omega : \phi(x,y,t) > 0\}$$

Using an initialization of the level set function based on the initial contour, it is iteratively approximated by minimizing an energy functional.

III. PCA FOR FEATURE EXTRACTION

PCA is a powerful technique for extracting structure from either high dimensional dataset. In fact, this can be performed by solving eigen value problem, or using iterative algorithms to estimate the principal components. It is considered as an orthogonal transformation in which the data will be described where used to transform a set of correlated variables into a set of uncorrelated variables. The new dataset values are called principal components. The number of principal components present after using PCA is either having the same number or lesser than the present original variables. In PCA, the largest possible variance can be found in the first component. Commonly, basic PCA uses linear transformations to map data from a high dimensional space of low dimensional space. The low dimensional space can be determined by eigenvectors of the covariance matrix. The steps involved in PCA include:

Step 1 Calculate the mean value of the given dataset ‘S’.

Step 2 Subtract the mean value from S. From these values a new matrix ‘A’ is obtained.

Step 3 Compute a covariance ‘C’ from ‘A’ using $C = AA^T$

Where, if the data 1,…,l $A_k \in R^N \bullet \sum_{k=1}^{l} A_k = 0$ the covariance matrix will be: $c = \frac{1}{l}\sum_{i=1}^{l} A_i A_i^T$

Step 4 The eigenvalues are obtained from the covariance matrixes, where are $[V_1, V_2, \ldots\ldots\ldots\ldots V_N]$

Step 5 Finally, eigenvectors are calculated for the covariance matrix C.

Step 6 Any vector S or $S - \overline{S}$ can be written as a linear combination of eigenvectors as:

$S - \overline{S} = b_1u_1 + b_2u_2 + b_3u_3 + \ldots\ldots + b_nu_n$ Since the covariance matrix is symmetric it has basis of the form $[V_1, V_2, \ldots\ldots\ldots\ldots V_N]$

Step 7 The lower dimensional dataset is obtained from the largest eigen values only are kept to form a

$$S - \overline{S} = \sum_{i=0}^{l} b_i u_i, l < N$$

The components in lower dimensional space are known as principal components. These principle components must be independent in case the dataset is normally distributed. PCA is generally sensitive to the scaling of the original variables.

IV. PROPOSED HYBRID ALGORITHM FOR SEGMENTATION FLDA AND LEVEL SET

1. Input Image
2. Preprocess the Image (de-noise the Image)
3. Find the mean of the obtained value de-noised dataset 'S'.
4. Subtract the mean value from S. From these values a new matrix 'A' is obtained.
5. Compute a covariance 'C' from 'A' using

$C = AA^T$ Where, if the data 1,…,l $A_k \in R^N \bullet \sum_{k=1}^{l} A_k = 0$

the covariance matrix will be: $c = \frac{1}{l}\sum_{i=1}^{l} A_i A_i^T$

6. The eigenvalues (Singular Values) are obtained from the covariance matrixes, where are $[V_1, V_2, \ldots\ldots\ldots.V_N]$
7. Finally, eigenvectors which uses the singular features, are calculated for the covariance matrix C.
8. Any vector S or $S - \overline{S}$ can be written as a linear combination of eigenvectors as:

a. $S - \overline{S} = b_1u_1 + b_2u_2 + b_3u_3 + \ldots\ldots + b_nu_n$ Since the covariance matrix is symmetric it has basis of the form $[V_1, V_2, \ldots\ldots\ldots.V_N]$

b. The lower dimensional dataset is obtained from the largest eigenvalues only are kept to form a

5.

$$S - \overline{S} = \sum_{i=0}^{l} b_i u_i, l < N$$

c. Apply LDA for further feature Processing to obtain the distinct features.

$$S_B = \sum_{i=1}^{C} n^i (\overline{X_l} - \overline{X})(\overline{X_l} - \overline{X})^T$$

$$S_W = \sum_{i=1}^{C} \sum x_i \in n^i (\overline{X_l} - \overline{X})(\overline{X_l} - \overline{X})^T$$

$$E_{optimal} = \arg\max_E \frac{|E^T S_B E|}{|E^T S_W R|} = [e_1, e_{2,} \ldots\ldots e_{C-1}]$$

$$p = E_{optimal}^T U^T Z$$

9. Project the obtained features in the image space and cluster the features and reconstruct the image *I*

/* Apply the variational Level Set method for segmentation*/

10. Let I be an image, and g be the edge indicator function defined by,

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2}$$

Then find coefficient of the internal energy term that help contour to outside the object boundary.

11. A contour (or level set) *C(t)* is a curve described by a set of points where the function has similar features . The zero level set can be given as

$$C(t) = \{(x, y) \in \Omega : \phi(x, y, t) = 0\}$$

where t is a variable that indicates the time step in the evolution of the contour.

$$inside(C) = \Omega_1 = \{(x, y) \in \Omega : \phi(x, y, t) < 0\}$$

and

$$inside(C) = \Omega_1 = \{(x, y) \in \Omega : \phi(x, y, t) > 0\}$$

10. Classify the Features according the properties also known as segmentation.

V. RESULTS

Using an initialization of the level set function based on the initial contour, it is iteratively approximated by minimizing energy functional. The energy functional is a measure of the deviation of the existing contour from the ideal contour according to image features .

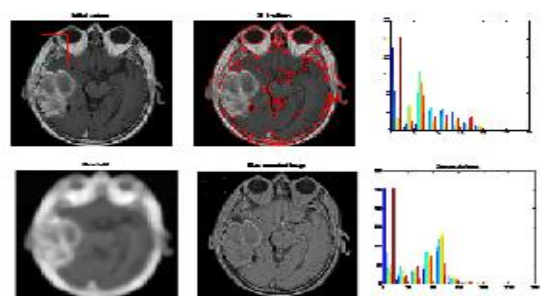

Fig.5.1.Segmentation with Level Set with Bias Correction

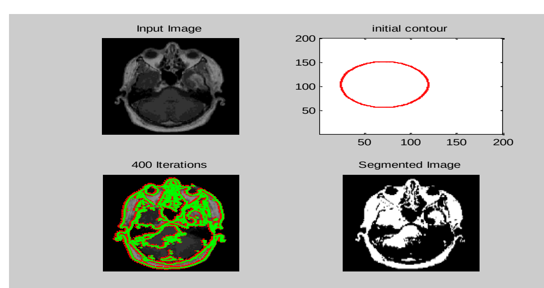

Fig.5.2. Segmentation with Level Set with FLDA

Table 1: Performance Analysis

Image	Mean	Standard Deviation	RMS	Variance	Smoothness	Energy
Lungs-Sec-5	0.0031107	0.0897608	0.0898027	0.0080479	0.930457	0.7621
Lungs-Sec-4	0.0032427	0.0897562	0.0898027	0.0080186	0.923447	0.740911
Lungs-Sec-3	0.0020681	0.0897909	0.0898027	0.0080305	0.884969	0.769087
Lungs-Sec-2	0.0019318	0.0897939	0.0898027	0.0080519	0.877845	0.749118
Lungs-Sec-1	0.0019393	0.0897938	0.0898027	0.0079872	0.87826	0.755387

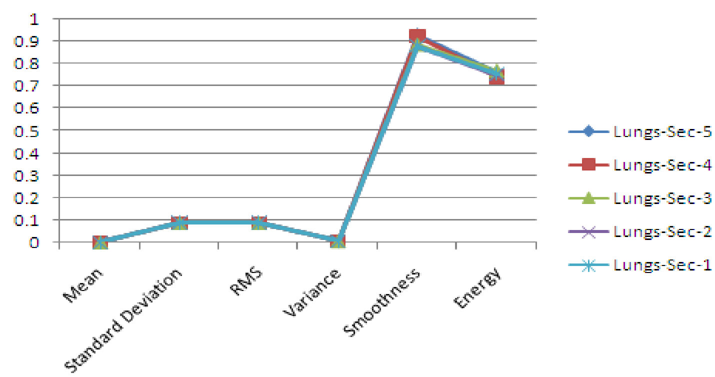

Fig 5.3. Performance showing the Smoothness of Hybrid Algorithm

VI. REFERENCES

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