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AN OPTIMAL SEGMENTATION AND CLASSIFICATION FOR TUMOR DETECTION

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Abstract— **Medical image segmentation algorithms frequently face difficult challenges such as poor image contrast, noise, and missing or diffuse boundaries. Similar problems arise in other imaging applications as well and they also hinder the segmentation of the image. In this paper, introduce a level set segmentation for increase the segmentation accuracy. It also implemented in lung part for process of segmentation. Further increase the segmentation accuracy, we using K-NN algorithm. This algorithm also used to detect the tumor in lung part and to minimize the energy functional for medical image segmentation. And we achieve the better Area Estimation with reduced time by interfacing KDE with Mean Curvature. The segmentation framework into a system for revealing and Classification of some diseases using Medical images like Tumor, Spinal Fraction, Stroke, etc.,**

***Index Terms*— K-Nearest Neighbor (K-NN), Kernel Density Estimation (KDE), Self Organizing Map (SOM), Support Vector Machine (SVM).**

I. INTRODUCTION

Medical imaging is the system and process of create visual representations of the interior of a body for clinical investigation and medical involvement. Medical imaging also establishes a database of normal anatomy and physiology to compose it possible to identify abnormality. Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are usually measured part of pathology instead of medical imaging. Under such conditions, without a former replica to constrain the segmentation, most algorithms (including intensity- and curve-based techniques) fail-mostly due to the under-determined natural world of the segmentation method. Similar problems arise in other imaging applications as well and they also delay the segmentation of the representation. These image segmentation problems demand the incorporation of as much earlier information as possible to help the segmentation algorithms extract the tissue of interest. We propose such an algorithm, In particular, we derive a model-based, implicit parametric representation of the segmenting curve and calculate the parameters of this representation via gradient descent to minimize an energy functional for medical image segmentation. Further increase the segmentation accuracy and also detect whether the tumors are affect or not in lung part of human body.

II. RELATIONSHIP TO PRIOR WORK

Our work shares common aspects with a number of model based image segmentation algorithms in the literature.

A. Point Distribution Model

A parametric point distribution model for relating the segmenting curve by means of linear combination of the eigenvectors that reflect variations from the mean shape. The shape and pose parameters of this point distribution model are determined to match the points to strong image gradients.

B. Statistical Point Model

More recently, Wang and Staib developed a statistical point model for the segmenting arc by applying principal component analysis (PCA) to the covariance matrix that capture the statistical variations of the landmark points. They formulate their edge-detection and correspondence-determination problem in a maximum *a posterior* Bayesian framework. Image gradient is used within that framework to calculate the fake and contour parameters that describes their segmenting curve.

C. Model Based Segmentation

It has a less restrictive model-based segmentation. They incorporated shape information as a prior copy to check the flow of the geodesic active contour. Their prior parametric shape model is derived by performing PCA on a gathering of signed distance map of the guidance shape. The segmenting curve then evolves according to two contending forces: 1) the incline force of the image, and 2) the force exerted by the estimated shape where the parameters of the shape are planned based on the image gradients and the current position of the curve.

D. Region-Based Segmentation

Our effort is also strongly related to region-based active contour models. In general, these region-based model enjoy a number of gorgeous property over incline based technique for segmentation, including greater robustness to noise (by avoid derivative of the image concentration) and original contour placement (by being less local than most edge-based approaches). Our novel editing techniques are founded upon the representation of an embedding scalar field associated with a few section of the point-set exterior. In evaluation with the pure, explicit point-based surface representation, the scalar field-driven secreted representation and level sets have been proven as a very powerful paradigm that can not only be free of charge of parameterization artifact, but also handle arbitrary topology and complicated geometry easily. In our level-set based surface editing framework, we exploit unstructured point samples as the basic modeling and rendering primeval all over this paper. By construct an inherent surface from the point cloud using some existing techniques, we can obviously include the level-set-based surface editing techniques into the deformation framework of the peak base geometry, which not only offer us a wide range of dominant surface editing techniques for the point set surface editing, but also facilitate the topology change with ease. Equipped with the level-set editing functionality, Scalar Free-Form Deformations (SFFD) can be also incorporated into our surface deformation system in order to further expand the ability for both narrow and overall surface editing. With the aid of dynamic re-sampling, we can quickly update the surface contour of the point-based geometry (undergoing geometric deformation and/or topological change) without worrying about point connectivity at all.

E. Parametric Point Model

A parametric point model based on an elliptic Fourier decomposition of the marker points. The parameters of their arc are calculated to optimize the match between the segmenting curve and the gradient of the image.

III.CONTOUR SPECIFICATION

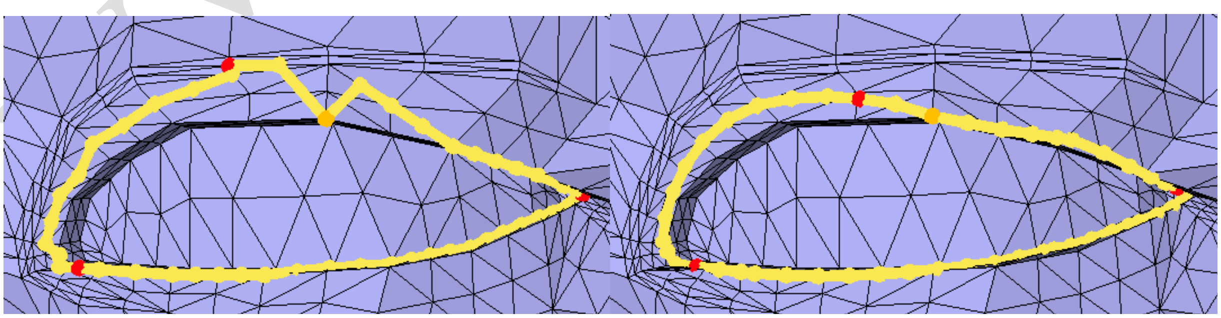
A. Snakes or Active Contour Model

The technique of *snakes* or *active contours* has become quite popular for a variety of applications in the past few years. This methodology is based leading the utilization of deformable contours which conform to various object shapes and motions. Snakes have been used for edge and curve recognition, segmentation, shape modeling, and visual tracking. Active contours have also been commonly applied for various applications in medical imaging. For example, snakes have been employed for the segmentation of myocardial heart margins as a prerequisite from which such vital information such as ejection-fraction ratio, heart output, and ventricular quantity ratio can be computed. we will apply anew snake paradigm which the authors have developed for edge detection and segmentation of various kinds of medical imagery including magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound.

In the classical theory of snakes, one considers energy minimization methods where controlled continuity splices are allowed to move under the influence of external image dependent forces, internal armed forces, and certain constraints set by the user. As is well known, there may be a number of problems related with this approach such as initializations, survival of multiple minima, and the selection of the elasticity parameter. Besides, natural criterion for the splitting and merging of contours (or for the treatment of multiple contours) is not eagerly available in this framework. In this work, we will apply a new active contour method which was developed. Our method unifies the curve evolution approaches for active contour and the classical energy methods mentioned. Because the geometric curve evolution equations can in fact treat merging and splitting of contours, our model gives the user the potential of repeatedly handling topological changes within the gradient flow energy framework. These model will only slow down the active contour at an edge, and so the snake will in general pass through the desired feature. Our model handles the topological complexities while providing *extra stopping power* to the capture the features of interest, based on first morality from geometric energy minimization. Mathematically, this amounts to defining a novel metric in the plane customized to the given image and then computing the corresponding gradient flow. This leads to a few new snake models which efficiently magnetize the given active contour to the features of interest (which basically lie at the bottom of a *prospective well*). Further, the method allows us to naturally write down three-dimensional (3-D) active surface models for 3-D image segmentation.

B. User Interaction

Our geometric snake model provides three user interaction techniques: snake initialization, point editing, and point fixing. The snake initialization is used to specify the initial position of a snake. When the user selects a sequence of vertices on a mesh near a desired feature, a closed or open curve is automatically build by relating closest vertices in the sequence with the shortest paths through the edges of the mesh. With point cutting, the user can direct a point of a snake to a preferred feature. For example, in Fig. 1, the user wants to detect the eyelid using the snake, but a few snake point have been attracted to the eyebrow. Then, the user can edit a snake point to change its location from the eyebrow to the eyelid, as shown in Fig. 1(a). After the editing, the snake points approximately the edited point moves collectively toward the eyelid due to the spline energy *Espline*. Fig. 1(b) shows the resulting arrangement from which the snake can finally confine the eyelid. The point fixing allows a point of a snake to be fixed at a exact location on the mesh in the energy minimization process. For example, in Fig. 1, the edited snake point is fixed at the stimulated location after editing. The point fixing is useful to protect snake points that already capture part of a preferred feature from location change in minimizing the spline energy *Espline*.



(a) Editing a point (b) Updated position

Fig 1: *Editing a snake*

C. Description Points For Segmentation

Step1: Sign Distance Function (φ)

Step2: Image Pixel range *z* to set of gray level values

$\{1, 2, ..., 256\}$.

Step3: Kernel Function

$$K(z - I(x)) = \delta_\varepsilon (z - I(x))$$

$$\delta_\epsilon(\phi) = \begin{cases} 0 & \phi > \epsilon, \quad \phi < -\epsilon \\ \frac{1}{2\epsilon}(1 + \cos(\frac{\pi\phi}{\epsilon})) & \text{otherwise} \end{cases}$$

Step4: Heaviside Step Function

$$H_\varepsilon(\phi) = \begin{cases} 1 & \phi > \epsilon \\ 0 & \phi < -\epsilon \\ \frac{1}{2}(1 + \frac{\phi}{\epsilon} + \frac{1}{\pi}\sin(\frac{\pi\phi}{\epsilon})) & \text{otherwise} \end{cases}$$

Step5: Probability Density Function

$$p_{in}(z,\phi) = \int_\Omega \frac{K(z - I(x))H_\epsilon(-\phi)}{H_\epsilon(-\phi)} dx \qquad p_{out}(z,\phi) = \int_\Omega \frac{K(z - I(x))H_\epsilon(\phi)}{H_\epsilon(\phi)} dx$$

Step6: Mean Curvature Energy Model

$$E_{image}(z,\phi) = \sqrt{\mathcal{E}\left\{\left(\log\frac{p_{in}(z,\phi)}{p_{out}(z,\phi)}\right)^2\right\} - \mathcal{E}\left\{\left(\log\frac{p_{in}(z,\phi)}{p_{out}(z,\phi)}\right)\right\}^2}$$

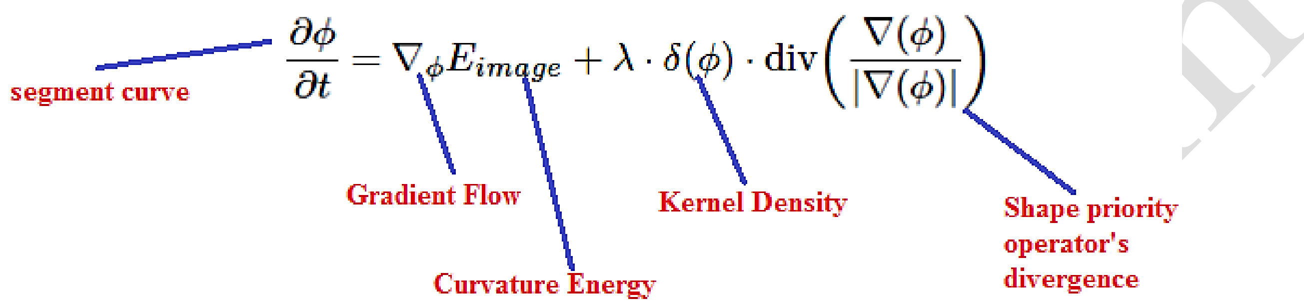
ε- is the mean function denotion

Step7: Gradient flow

$$B = \log\frac{p_{in}(z,\phi)}{p_{out}(z,\phi)}$$

$$\nabla_{\phi} E_{image} = -\frac{\delta_{\epsilon}(\phi)}{E_{image}} \cdot [\mathcal{E}\{B \cdot G\} - \mathcal{E}\{B\} \cdot \mathcal{E}\{G\}]$$

Step 8: Level set with final snake model



$$\frac{\partial \phi}{\partial t} = \nabla_{\phi} E_{image} + \lambda \cdot \delta(\phi) \cdot \text{div}\left(\frac{\nabla(\phi)}{|\nabla(\phi)|}\right)$$

IV. K-NN ALGORITHM

For increase the segmentation accuracy, We use KNN algorithm.

In pattern recognition, the ***k*-Nearest Neighbors algorithm** (or ***k*-NN** for small) is a non-parametric technique used for classification and regression. In both cases, the input consists of the *k* nearby guidance examples in the feature space. The output depends on whether *k*-NN is used for classification or regression.

A. Classification

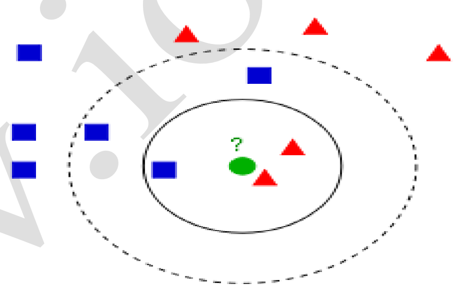


Fig 2:Example of K-NN classification**.**

The test sample (green circle) should be classified either to the first set of blue square or to the second set of red triangles. If $k = 3$ (solid line circle) it is assigned to the second set because there are 2 triangles and only 1 square inside the inner circle. If
$k = 5$ (dashed line sphere) it is assigned to the first set (3 squares vs. 2 triangles inside the outer sphere).

The training examples are vectors in a multi dimensional feature space, each with a class label. The training phase of the algorithm consists only of store the feature vectors and class labels of the training samples. In the classification phase, *k* is a user-defined identical, and an unlabeled vector (a query or test point) is classified by assigning the label which is most recurrent among the *k* training samples adjacent to that query point.

A commonly used distance metric for continuous variables is Euclidean distance. For distinct variables, such as for text classification, another metric can be used, such as the **overlie metric** (or Hamming distance). Within the context of gene expression microarray data, for example, *k*-NN has also been engaged with correlation coefficients such as Pearson and Spearman. Often, the classification precision of *k*-NN can be improved extensively if the distance metric is learned with specialized algorithms such as Large Margin Nearest Neighbor or Neighborhood components analysis.

A drawback of the basic "majority voting" classification occurs when the class circulation is twisted. That is, examples of a more frequent class tend to dominate the prediction of the new example, since they tend to be common between the *k* nearest neighbors due to their large number. One way to conquer this problem is to weigh the classification, taking into account the distance from the test point to each of its *k* adjacent neighbors. The class (or rate, in regression problems) of each of the *k* nearest points is multiplied by a weight relative to the converse of the distance from that point to the test point. Another way to conquer skew is by concept in data demonstration. For example in a self-organizing map (SOM), each node is a delegate (a center) of a cluster of similar point, regardless of their density in the original training data. *K*-NN can then be applied to the SOM.

B. Properties

K-NN is a special case of a variable-bandwidth, kernel density "balloon" estimator with a identical kernel. The naive adaptation of the algorithm is easy to implement by computing the distances from the test example to all store examples, but it is computationally intensive for large training sets. Using a suitable nearest neighbor search algorithm make *k*-NN computationally tractable even for large data sets. Many nearest neighbor search algorithms have been planned over the years; these generally seek to reduce the number of distance evaluation essentially performed. *k*-NN has some tough consistency consequences. As the amount of data approaches infinity, the algorithm is assured to yield an error rate no worse than twice the Bays error rate (the minimum achievable error rate given the distribution of the data).

V. IMPLEMENTATION AND RESULTS

There are having three stages of implementation

A. Training

In this stage we having number of database atlas images

1. Calculate mean curvature image as per the below block diagram
2. Registration of images nothing but the feature storage of atlas area.

B. Testing

1. As per the below process we need to get the features of query(ie. single image)
2. Registration and deformation with the number of Database images
3. Deformation is the last step of this flow diagram active contour model

C.Validation

Finally we have number of contour shape as per the testing stage registration and finally we select one segmented model based on the high matching rate image.

D.Simulation Results

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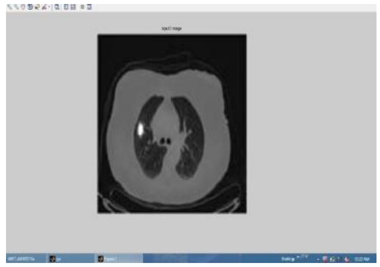

Fig 3: Input Image

Fig 4:Binary Image

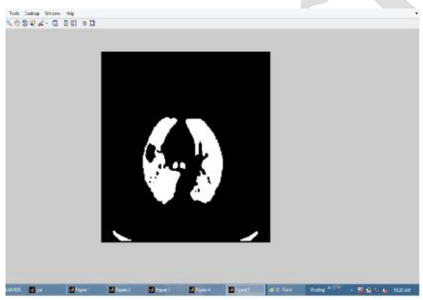

Fig 5: Lung Segmentation

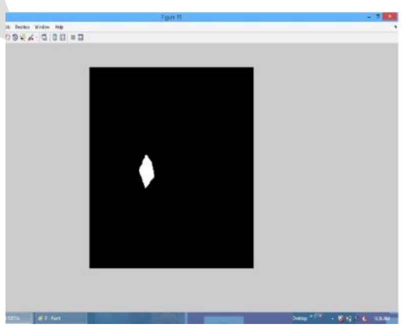

Fig 6: Masking

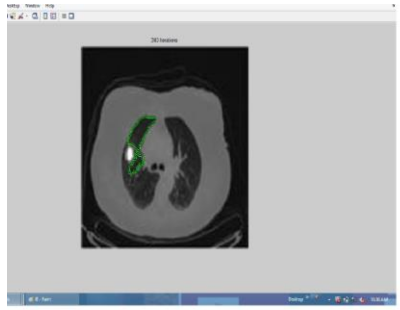

Fig 7 Iterations

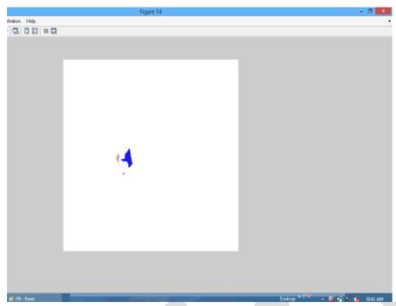

Fig 8: Feature Extraction

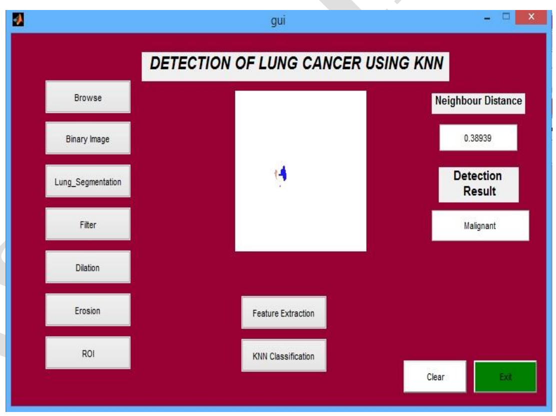

Fig 9: K-NN Classification

VI. CONCLUSION

We have offered a latest segmentation framework based on the level set for Medical Image segmentation. The frameworks incorporate not only prior contour knowledge through the KDE method, but also local geometrical features through Mean Curvature Energy model, into the level set segmentation. Experimental results on MRI, CT and Ultrasound images, validated with ground truth, display the effectiveness of proposed framework. The framework has achieved much higher segmentation accuracy (92.517%) than existing methods, such as Chan–Vese and Caselles, region growing, and graph cut. And we achieve the better Area Estimation with reduced time by interfacing KDE with Mean Curvature.

Ongoing research includes integrating the segmentation framework into a structure for revealing and Classification of some diseases using Medical images like Tumor, Spinal Fraction, Stroke, etc., .and also increase the segmentation accuracy using support vector machine(SVM) algorithms.

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