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Robust MRI Brain Segmentation with an Application to Tumor Segmentation and Classification

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***Abstract* – A novel segmentation model that considers global and local image statistics. The global energy derived from a Gaussian model estimates the intensity distribution of the target object and background. The local energy is derived from mutual influences of neighboring pixels. The robustness of this method is validated on segmenting images with/without intensity homogeneities. Image segmentation is the process of assigning a label to every pixel in an image such that each pixel with the same label shares certain visual characteristics. Later, we further classify the tumor using Eigengene-Based Classifier Committee Learning Algorithm. Gene expression data constructed by different feature subspaces are modeled by ICA, respectively. The corresponding eigengene sets extracted by the ICA algorithm are used as the inputs of the weaker SVM classifiers. Quantitative experimental comparisons demonstrate that the proposed method (GLE) is more robust and more accurate in segmenting the images with intensity inhomogenities than the local binary fitting, locality sensitive hashing techniques also outperformed the region based Chan-Vese model when dealing with images without intensity inhomogenities and produce better segmentation results.**

***Keyword* – Classifier Committee Learning Algorithm, Eigengene-Based Extraction, Energy Minimization, Gaussian distribution, Global and Local Energy Function, Image Segmentation, Level Set Formulation.**

I. INTRODUCTION

Image Segmentation is the process of digital image into multiple segments. It is assigning a every pixel such that each pixel assigning a same label and certain visual characteristics. The result of image segmentation is collectively covering the entire image or the contour extracted from the given image. Level set methods capturing interfaces and shapes. The main idea of the level set function is to represent a contour has a higher dimensional of the zero level set function. The level set energy function is minimized the process of evolving the contour on the basis of edge energy to stop on the desired boundary via the boundary detector or region-based energy.

It is not depending on the edge base detectors, it is only depending on region base detectors. In general robust energy models challenging, due to limited poor contrast, spatial resolution, variety of image noise and intensity inhomogeneities.

A new model of active contours or shakes is to evolve curve subject constraints from the given image [8]. It is used for in order to detect the object in that image. A curve is starting with around the object to be detected. The curve moves towards interior normal and has to be stopped on the desired boundary. It can detect the objects whose boundaries are not necessary defined by gradient [9].

The problem of simultaneous image segmentation and smoothing by approaching the Mumford-Shah functions from a curve evaluation [4]. In particular a set of deformable contours defined the boundaries between the regions in an image where model the data via piecewise smooth functions and employ a gradient flow to evolve these contours [1].

A Chan-Vese region based method for extracting useful information from microscopic images under complex condition was presented. The method incorporates a local binary fitting model into a maximum regional difference model. It utilizes both local and global intensity information as the driving forces of the contour model on the principle of the largest regional difference [3].

Shape models aid the tasks of the object representation and recognition. A shape modeling which retains some of attractive features of existing methods and overcomes some of their limitations was presented [5]. It can be applied to model arbitrary complex shapes which include shapes with significant situations where no a priori object topology is made [6].

Level set methods can be widely used in Image Processing and computer vision. In conventional level set formulations, it is typically develops irregularities during it is evolution [2].

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The level set method is derived as the gradient flow that minimizes energy functional with distance regulation term and an external energy derives the zero level set toward desired locations.

In this paper, we propose segmented images with/without intensity inhomogenities and with Gaussian noise. It is dominated by the global Gaussian distribution and constrained by local neighbor properties. It overcomes the artifacts from both image noise and intensity inhomogenities. The rest of the paper is organized as follows. Section 2 and Section 3 describe system model and methodologies respectively. Section 4 presents the performance evaluations and experimental results for the proposed approaches. Finally, section 5 gives conclusion.

II. SYSTEM MODEL

A) Global and Local Energy Segmentation Model

Global and local energy can be assumed that the intensity values of different regions of the same object can be modeled as a finite Gaussian distribution. Under this assumption, all the pixels belonging to the same distribution would be assigned to the same class and our energy function is defined as below.

$$E(C,G,b) = \sum_{i=1}^{M} \int_{\Omega_i} \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(I(x)-b(x)\mu_i)^2}{2\sigma_i^2}\right) dx \quad (1)$$

Where G *is* a full set of Gaussian parameters: μ_i and σ^2_i are the Gaussian mean and the variance for the object i respectively.

The noise would be further reduced when the contextual constraint is taken account as the classification. Then the spatial property is incorporate with the Gaussian model to improve the intensity to the noise of as below.

$$E^{\text{lg}} = \int \left(\sum_{i=1}^{M} \int_{\Omega_i} Z(|z-x|) \frac{1}{\sqrt{2\pi}\sigma_i} \times \exp\left(-\frac{(I(x)-b(x)\mu_i)^2}{2\sigma_i^2}\right) dx \right) dz \quad (2)$$

In the above equation Z $(|z - x|)$ is the convolution kernel.

Then generate the MRF model to provide a convenient and consistent way to characterize mutual influences among the pixels. The impact of noise would be further reduced account as the classification weight of each pixel.

$$Z(x) = \alpha \exp\left(-\sum_{c\in C} U_c(x)\right) = \alpha \exp\left(-\sum_{(i,j)\in C} t(x_i, x_j)\right) \quad (3)$$

Where α is a normalizing constant is a sum of clique potentials $U_c(x)$ over all possible cliques C.

Finally the energy functional is formulates as given below.

$$E^{\text{lg}} = \int \left(\sum_{i=1}^{M} \int_{\Omega_i} \frac{Z(|z-x|)}{\sqrt{2\pi}\sigma_i} \exp(-e_i(x))\, dx \right) dz \quad (4)$$

The influence of neighborhood pixels in the predefined local window depending on their spatial distance from the central pixel is calculated by using correlation kernel.

System architecture for the Global and Local Energy Segmentation and Tumor Classification using Eigengene-Based Classifier Committee Learning Method (shown in Figure 1). Given any type of input image to apply the Gaussian noise on that image, it will become a noisy image. Then we have to apply the global and local energy function. The energy is presented as a level set framework by representing disjoint regions with a number of level set functions. The energy minimization can be solved by using the curve implicitly via the level set framework.

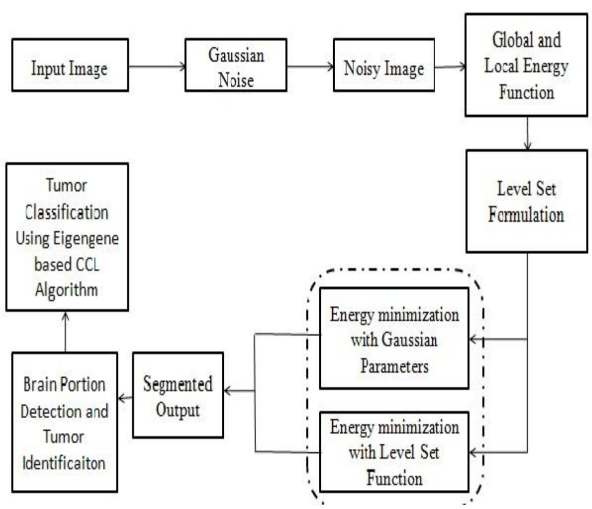

Figure 1. Global and Local Energy Segmentation and Tumor Classification using Eigengene-Based Classifier Committee Learning Method

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Energy minimization with respect to Gaussian parameters is equivalent to the minimum likelihood, which requires the minimization of the log-likelihood function. To minimize the energy functional E with respect to the Euler-Lagrange equations is applied. A standard method to minimize a fitting form E is to find the steady state solution of the gradient flow equation by iteration t. Finally to classify the tumor based on Global and Local Energy Function. Further to improve the tumor classification using Eigengene Based Classifier Committee Learning Algorithm.

III. Methodologies

In this section, we discuss Level Set Formulation, Minimization of the Energy Function, Energy minimization with Gaussian parameters and Energy minimization with level set function. Tumor Classification Using Eigengene-Based CCL Algorithm.

3.1 Level Set Formulation

In the level set framework, the energy minimization can be solved by using the curve implicitly via the level set function. It takes positive and negative signs, which can be used to represent a partition of the domain into two disjoint regions. Ω_1 and Ω_2 where $\Omega_1 \cup \Omega_2 = \Omega$, $\Omega_1 \cap \Omega_2 = \Phi$, and this level set function is called two-phase. If more than one level set function is presented, the multiphase formulation is required. The Heaviside function H allows the level set function to take opposite signs and represents the membership of two disjoint regions Ω_1 and Ω_2 by $R_1(\Phi(x))=H(\Phi(x))$ and $R_2(\Phi(x))=1-H(\Phi(x))$ respectively. Under the variation level set formulation and minimization purpose, the above proposed energy E_{lg} is used as the data term. The level set framework is represented as Φ.

$$E^{lg}(\phi, b, G) = \int \left(\sum_{i=1}^{2} \int_{\Omega_i} \frac{Z(z)}{\sqrt{2\pi}\sigma_i} \times \exp\left(-\int \frac{W(y)\,(I(x) - b(y)\mu_i)^2}{2\sigma_i^2} dy \right) \times R_i(\phi(x))\,dx \right) dz. \tag{5}$$

The other two regularization terms to regulate the level set function in our proposed energy functions.

$$E = E^{lg} + \upsilon \int |\nabla H(\phi(x))|\,dx + \beta \int p(|\nabla \phi(x)|)dx \tag{6}$$

Where $v \geq 0$ is the constant of the smoothness term and the length of the zero level set contour of Φ as the smoothness term.

3.2 Minimization of the Energy Function

It can be obtain the optimized result of image segmentation given by the level set function. The energy minimization is achieved by iterative process. It give the solution to the energy minimization with respect to its variables Φ, b, μ_i and σ_i for inside and outside the contour.

A) Energy Minimization with Gaussian Parameters

Algorithm:

1) To find the energy minimization based on Gaussian parameters.
2) First find the Gaussian mean.
3) Calculated μ_i by using the below formula
4) To keep φ and b fixed to minimize the energy form E with respect to the region descriptor μ_i and σ_i

$$\hat{\mu}_i = \frac{\int (b * W)\, I R_i(\phi)\, dx}{\int (b^2 * W)\, R_i(\phi)\, dx}$$

5) Next calculate the σ_i by using the below formula

$$\hat{\sigma}_i^2 = \frac{\int W * (I - b\hat{\mu}_1)^2 R_i(\phi)\, dx}{\int R_i(\phi)\, dx}$$

6) In the above equation * is the convolution operation.
7) And $(\hat{\ })$ are denoted as the intermediate values for the variables during each iteration of optimization.
8) After calculating μ_i and σ_i next find the bias field b.
9) To keep φ and the region descriptors μ_1, μ_2 and σ_1, σ_2 fixed to minimize the energy form E with respect to the bias field b.
10) Finally the bias field b is calculated by using the below formula

$$\hat{b} = \frac{\left(\left(\frac{\mu_1}{\sigma_1^2} R_1(\phi) + \frac{\mu_2}{\sigma_2^2}(\phi) \right) I \right) * W}{\left(\frac{\mu_1^2}{\sigma_1^2} R_1(\phi) + \frac{\mu_2^2}{\sigma_2^2} R_1(\phi) \right) * W}$$

B) Energy Minimization with Level Set Function

Algorithm:

1) To minimize the energy functional E with respect to φ.
2) To apply the associated Euler-Lagrange equation for φ is applied.

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3) Then to minimize a fitting form E is to find the steady state solution of the gradient flow equation by iteration t.
4) In energy minimization with respect to the Level set function find the Gaussian kernel w using the below formula.

$$W(|y-x|) = \frac{\gamma}{1 + \frac{1}{\sqrt{2\pi\omega^2}} e^{\frac{(y-x)^2}{2\omega^2}}}$$

3.3 Tumor Classification Using Eigengene-Based CCL Algorithm

Eigengene extracted by independent component analysis (ICA) is one kind of effective feature for tumor classification. A novel tumor classification approach is proposed by using eigengene and support vector machine (SVM) based classifier committee learning (CCL) algorithm. In this method, a strategy of random feature subspace division is designed to improve the diversity of weaker classifiers.

Algorithm:

1) Divide the data into training data and test data.
2) Perform the cross-validation on the training data to find the approximate optimal percentage with the largest classification rate of the validation set.
3) Randomly select the given number of genes and form the new training data and test data to extract the eigengene matrix from the training data using the ICA algorithm to compute the eigengene matrix.
4) Train SVM using the training samples; get the optimal parameters by combining the v-fold cross-validation and the grid-search.
5) Obtain the posterior probability matrix of the Training data and of the test data using the trained SVM.
6) Compute the sum of probability testing data values to get the label of the testing data with the maximum operation. Then to compute the classification rate.

IV. Performance Evaluations

In this section, we evaluate the performance of the proposed method several performance metrics are available. The Chan vese (CV), Local Binary Fitting (LBF), Locality Sensitive Hashing (LSH), proposed method (Global and Local Energy Segmentation) are compared to analyses the performance.

The proposed system is implemented using a mat lab program where it is evaluated for segmenting the image. The performance of the algorithm is evaluated on several real images.

4.1 Performance Measures

A) True Positive (TP): It is the proportion of positive cases that were correctly identified, known as true positive.

B) True Negative (TN): It is defined as the proportion of negatives cases that were classified correctly, known as true negative.

C) False Positive (FP): It is the proportion of negatives cases that were incorrectly classified as positive, known as false positive.

D) False Negative (FN): It is the proportion of positives cases that were incorrectly classified as negative, known as false negative.

E) Accuracy value: The accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's actual (true) value.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Table I
Comparison Over Noisy Synthetic Images Over Four Models

Segmentation Models	Accuracy Values
Chan Vese	0.29
LBF	0.45
LSH	0.73
Proposed method(GLE)	0.88

The proposed method performs well than the existing method. Because it has high accuracy value than the existing method.

F) Error value: The error value measurement of a system is the degree of closeness of measurements of a quantity to that quantity's actual (false) value.

$$\text{Error} = \frac{FP + FN}{TP + TN + FP + FN}$$

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Table II
COMPARISON OVER NOISY SYNTHETIC IMAGES OVER FOUR MODELS

Segmentation Models	Error Rates
Chan Vese	60
LBF	52
LSH	35
Proposed method(GLE)	10

The proposed method performs well than the existing method. Because it has low Error value than the existing method.

4.2 Experimental results

In the proposed system a general energy model to segmented images with and without intensity inhomogeneities and a variety of image noise by balancing the energies from local and global contributions have been proposed. The proposed local energy determines the relationship between spatial influence and gray values simultaneously to compensate intensity inhomogeneities. Incorporated with the local energy, the novel global statistic energy better describes both target and background to provide robust region estimation and also reduces the sensitivity to image noise. Through minimization of the proposed energy functional, implicit contour would be evolved to perform image segmentation under the level set framework. It has proposed a more general model for segmenting images with/without intensity inhomogeneities and with different types of noise. The proposed level set energy function which is dominated by the global Gaussian distribution and constrained by local neighbor properties, can overcome the artifacts from both the intensity inhomogeneity and image noise. A quantitative accuracy, error comparison on synthetic images and experimental results on real images showed that proposed model (GLE) outperformed the CV, LBF and LSH models designed specifically for segmenting the images with intensity inhomogeneities as shown in Table I, and II. For the CV model, LBF model, LSH model, and the proposed model (GLE), we adopted the parameters settings according to their published implementation (shown in Figure 2).

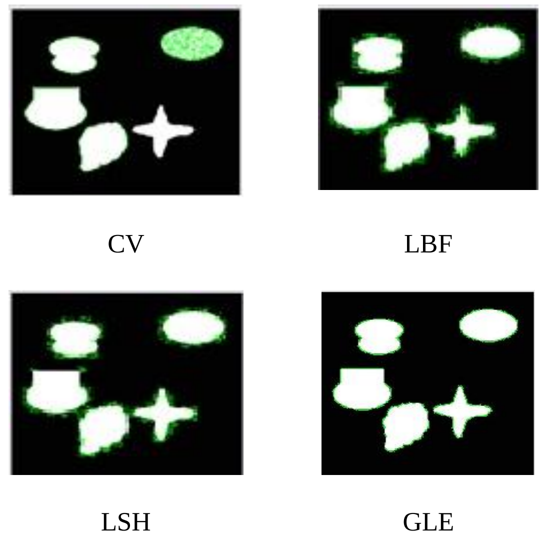

Figure 2. Segmentation results of four segmentation methods. The segmentation results (marked as green contours) of CV, LBF are shown in the 1st row and LSH, GLE (proposed method) are shown in the 2nd row respectively.

A) Description of Synthetic Images and Evaluation Measure

To quantitatively evaluate the proposed algorithm's accuracy, we built a synthetic image database that included 100 clean synthetic images. Each clean image contained up to number of disjoint regions of different shapes and at different spatial locations. The values of shading artifacts $b(x)$ varied slowly with values ranging from 0 to 1 and were used to corrupt the synthetic image by $I(x) = b(x)*I(x)$. From this database, image noise corrupted images and shading artifacts were generated by adding different levels and different types of noise and bias field. According to the noise $n(x)$ is assumed to be zero-mean Gaussian noise (GN) in our experiments. In proposed experiments, the types of image noise consist of zero mean Gaussian noise (GN). To evaluate the performance of the proposed method several performance metrics are available. The Chan vese(CV), Local Binary Fitting(LBF), Locality Sensitive Hashing(LSH), Proposed method(Global and Local Energy) are compared to analyses the performance of the GLE algorithm is evaluated on synthetic images. These different types of performance analysis (as shown in Figure 3, Figure 4).

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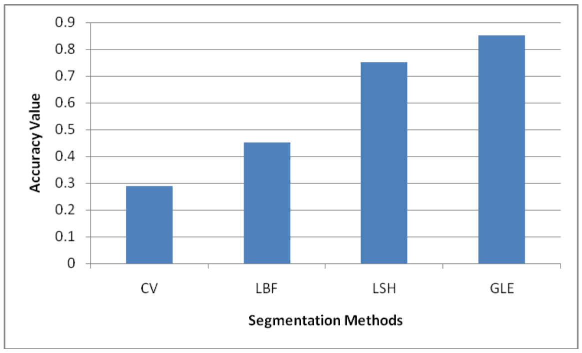

Figure 3. Accuracy value comparison over the CV, LBF, LSH and GLE models on the four different groups of synthetic noisy images.

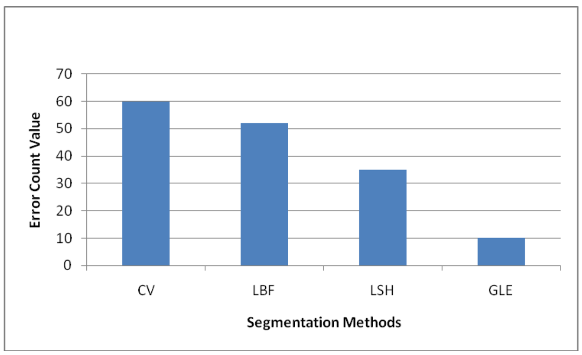

Figure 4. Error Count Value comparison over the CV, LBF, LSH and GLE models on the four different groups of synthetic noisy images.

V. CONCLUSION

In this paper, A more general model for segmenting images with/without intensity inhomogeneities and with different types of noise have been proposed. The proposed level set energy function, which is dominated by the global Gaussian distribution and constrained by local neighbor properties, can overcome the artifacts from both the intensity inhomogeneity and image noise.

A quantitative comparison on synthetic images and experimental results on real images showed that the proposed model (GLE) outperformed the LBF and LSH models designed specifically for segmenting the images with intensity inhomogeneities. It was more robust and accurate than the CV model when segmenting the images without intensity inhomogeneities. The above proposed algorithm can be implemented for tumor classification.

REFERENCES

[1] A. Tsai, A. Yezzi, and A. S. Willsky, “Curve evolution implementation of the Mumford Shah functional for image segmentation, denoising, interpolation, and magnification,” IEEE Trans.Image Process., vol. 10, no. 8, pp. 1169–1186, Aug. 2001.

[2] C. Li, C. Xu, C. Gui, and M. D. Fox, “Distance regularized level set evolution and its application to image segmentation,” IEEE Trans. Image Process., vol. 19, no. 12, pp. 3243–3254, Dec. 2010.

[3] C. Li, C.-Y. Kao, J. C. Gore, and Z. Ding, “Minimization of regionscalable fitting energy for image segmentation,” IEEE Trans. Image Process., vol. 17, no. 10, pp. 1940–1949, Oct. 2008.

[4] D. Mumford and J. Shah, “Optimal approximations by piecewise smooth functions and associated variational problems,” Commun. Pure Appl. Math., vol. 42, no. 5, pp. 577–685, 1989.

[5] G. Song and T. D. Bui, “Image segmentation and selective smoothing by using Mumford-Shah model,” IEEE Trans. Image Process., vol. 14,no. 10, pp. 1537–1549, Oct.2005.

[6] R. Malladi, J. A. Sethian, and B. C. Vemuri, “Shape modeling with front propagation: A level set approach,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 17, no. 2, pp. 158–175, Feb. 1995.

[7] R. Tsai and S. Osher, “Level set methods and their applications in image science,” Commun. Math. Sci., vol. 1, no. 4, pp. 1–20, 2003.

[8] S. Lankton and A. Tannenbaum, “Localizing region-based active contours,” IEEE Trans. Image Process., vol. 17, no. 11, pp. 2029–2039,Nov. 2008.

[9] T. F. Chan and L. A. Vese, “Active contours without edges,” IEEE Trans. Image *Process.*, vol. 10, no. 2, pp. 266–277, Feb. 2001.

[10] Y. Boykov and V. Kolmogorov, “An experimental comparison of mincut/max-flow algorithms for energy minimization in vision,” IEEE Trans.Pattern Anal. Mach. Intell., vol. 26, no. 9, pp. 1124–1137, Sep. 2004.