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Gradient Vector Flow Analysis for Multimodality Medical Images

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Abstract: Medical image analysis is an emerging technique for diagnosis, surgical and treatment planning. These image computation methods lead the physician to isolate the unwanted tissues of the human organs. Every one of the patients are expecting without cutting, without bleeding and day care operations. So these scanned images are analyzed before preceding the treatment process. In this study, the image segmentation and classification are done for various medical images and Gradient Vector Flow based Multi-classifier (GVFM) has proposed and implemented by Matlab coding. The medical image analysis parameters sensitivity, specificity and accuracy are calculated for multimodality medical images.

Key words: Active contour model, gradient vector flow, image segmentation, edge detection, image classification

INTRODUCTION

Image classification and segmentation is widely used in medical fields for medical research, medical image diagnosis, treatment, therapy evaluation, surgical planning and pathological analysis. In medical field, it is necessary to extract the specific region from the medical image in computer vision. There are many solutions to select the particular portion of the images. Active Contour extraction method is one of the efficient techniques (Michailovich *et al*., 2007) for medical image analysis like edge based model, region based model and pixel based models. An active contour model was proposed and implemented by Kass, witkin and terzopoulos in1987. This model constructs an active contour over the image for extracting the specific portion (Chai *et al*., 2011). It is an algorithmic approach to compute any medical image segmentation and classification. Brain tumor segmentation technique can be used to segregate the tumor tissues from non tumor tissues. In bio medical imaging, it is very critical in surgical and treatment for curing process. There are significant types of malignant tumors are available in human brain. They appeared in varying with different shape, size and location of the different brain tumor such as astrocytoma, meningioma, glioma, medullo blastoma and metastatic. The affected tissues of the brain image are looking like darker than normal brain tissue (hypo-intense), same intensity as brain tissue (iso-intense) and brighter than the brain tissues (hyper-intense). Based on these variations on the image, segmentation process can used to segregate and locate the abnormal region of the brain. The detection of tumor size and estimation of tumor volume is the challenging problem to take the treatment of surgical or therapy process (Sachdeva *et al*., 2012). Before doing surgical operation or applying the therapy evaluation, classifier is essential for classify the tissues very efficiently.

Many research works carried out for the classification of brain diseases based on different sources of information. MRI can help doctors to diagnose the disease as it provides important information about the anatomy, function, perfusion and viability of the myocardium. MRI scan is one of the accurate measurements of disease detection throughout the body. MRI is a treat that uses a magnetic field and pulses of radio wave energy to make pictures of organs and structures inside the body. The MRI is a safe and painless test that uses magnetic field and radio waves to produce detailed pictures of body's organs and structures. X-Ray, Computed Tomography (CT) and Magnetic Resonance Image (MRI) are the most important bio medical images widely used radiographic techniques in diagnosis and treatment planning. Segmentation techniques used for the brain MRI is used to detect any abnormality in the brain. The specific region and classification are significant for physician or radiographer to analysis and diagnosis the level of the diseases. By this research analysis, doctors can easily isolate or remove the unwanted tissues from human body and also the surgical time reduced. Based on these recent techniques lead the patients to quick recover from the internal disease.

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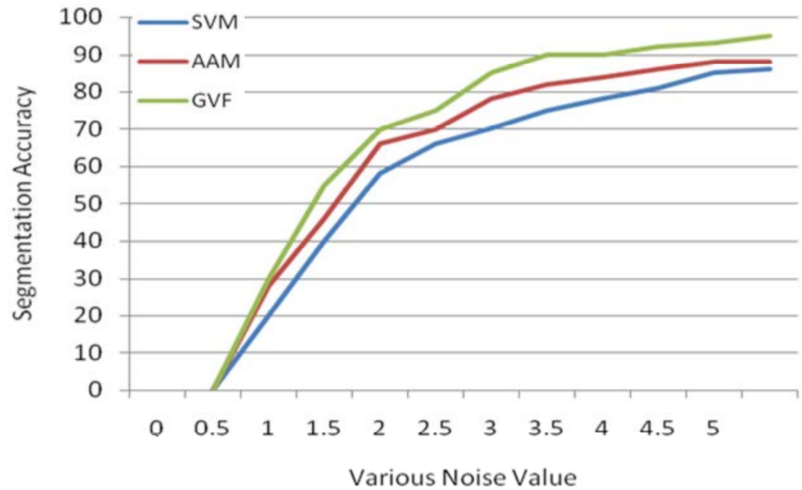


Fig. 1: Gradient vettor flow

Gradient vector flow based multi classifier: The segmentation of tumor images are performed by active contour models and it rudimental classified on two types based on its speed and range. The parametric set contour model can be fastly segmented in single objects which are gradient Vector Flow (GVF), Boundary Vector Flow (BVF) and Fluid Vector Flow (FVF). Xu proposed the gradient vector flow model in 1998. In this model, the external force is computed as a diffusion of the gradient vectors of gray level to binary edge map derived from the image. The GVF model has more significant improvements than the snake model which is widely used for medical image segmentation. Edge detection is one of the image analysis and computer vision (Dilip and Rupa, 2014). Edges are characterizing the selected object boundary based on their properties of intensity and texture can provide valuable information for further image processing for image analysis (Fig. 1).

Gradient vector flow model is related the geometry of indentation of boundaries with potential force computation (Ren *et al*., 2013). In this computation, when the pixels number of a long and thin boundary indentation is even, the GVF model cannot capture the indentation. When the pixel number is odd, the GVF model can capture the indentation (James and Dasarathy, 2014). In the GVF model, when the pixel number of the indentation is even, the force in vertical direction is counteracted by the force in horizontal direction. And when the pixel number of the indentation is odd number, the force is vertical direction still exists. In the boundary detection, GVF model cannot detect the boundaries like ‘U’ and ‘Ω’. Then some new algorithmic approach is added and computed for the boundary of brain image (Cheng and Sun, 2012).

MATERIALS AND METHODS

Energy of active contour model: The energy minimization process is the combination of both internal forces and external forces. The internal forces (Dwivedi *et al*., 2014) have elastic force and bending force whose primary role is to prevent the excessive bending curve. The important role of external force is to move the curve toward the boundaries of the image. This both forces will make the curve gradually arrive at the image characteristics region which is the edge of the image.

The external energy from E_{ext} is derived from the image so that it takes on its smaller values of the features of interest such as boundaries (Zhao *et al*., 2014). The gray level image I(x,y) is considered as a function of continuous position variables (x,y) and its external energies designed to lead an active contour toward step edges as Eq. 1 and 2:

$$E^1ext\ (x,y) = |\nabla I(x,y)|^2 \quad (1)$$

$$E^2ext\ (x,y) = |\nabla G_\sigma(x,y) \times I(x,y)|^2 \quad (2)$$

Where:

$\lvert\nabla I\ (x,y)\rvert = (G_x(x,y)^2 + G_y(x,y)^2)^{1/2}$	=	A gray level in (x,y)
$G_x(x,y) = I(x,y) \times M_x(x,y)$	=	Edge gradient of x direction
$G_y(x,y) = I(x,y) \times M_y(x,y)$	=	Edge gradient of y direction
$M_x(x,y)$, $M_y(x,y)$	=	The horizontal and vertical gradient mask

$G_\sigma(x,y)$ is the 2D Gaussian smoothing function with standard deviation **σ**, x is the convolution operator and ∇ is the gradient operator. To improve the ACM convergence into long, thin boundary indentation, Xu and Prince presented a generalized of GVF formulation (GGVF) model which is in the partial differential equation:

$$V_t = g(|\nabla f|)\nabla^2 v - h(|\nabla f|)(v - \nabla f) \quad (3)$$

The first term is referred as the smoothing term because this term can produce a smoothly varying vector field. The second term is referred as the data term since it encourages the vector field V to be close to f. the weighting functions g(.) and h(.) apply to the smoothing and data term respectively. The smoothed image in each scale can be acquired by the convolution of the smoothing filter with the image obtained in previous scale

RESULTS AND DISCUSSION

The contour must be initialized to initialize the external force field. The initial contour can be inside, outside or overlapping the target objects. GVF is insensitive to initialize by taking advantage of the binary boundary map. The contour C can be represented as in Eq. 3:

$$C(i) = \{(xi, yi)\}, i \in [0,1,....P-1) \quad (4)$$

The trace method has used to the binary boundary map to get a list of control points. The control points are used to generate the external force fields. GVF has the both directional and gradient forces. The directional force attracts the evolving contour toward the control points even for control points in a concave region. When the contour is close to the object, the gradient force fits the contour onto the object. One control point is sequentially selected and this point flows freely along the object boundary and generates an external force field dynamically. This computation is performed iteratively to extract the tumor. Table 1 shows the experimental results for various images to diagnosis the affected cells.

The performance of the classifier is measured in terms of sensitivity, specificity and Accuracy. Sensitivity is a measurement to determine the probability of the true positive in the tumor. Specificity is a measure to determine the probability of the results is in true negative such that a person does not have the tumor. Accuracy measure which determines the probability that how many results are accurately classified:

$$\text{Sensitivity} = \text{TP}/\ (\text{TP+FN}) \times 100\%$$

$$\text{Specificity} = \text{TN}\ (\text{TN+FP}) \times 100\%$$

$$\text{Accuracy} = (\text{TP+TN})/(\text{TP+FP+TN+FN}) \times 100\%$$

Positive likelihood ratio: ratio between the probability of a positive test result given the presence of the disease and the probability of a positive test result given the absence of the disease and Negative likelihood ratio: ratio between the probability of a negative test result given the presence of the disease and the probability of a negative test result given the absence of the disease The parameters determined by using these parameters like TP stands for True Positive, TN stands for True Negative, FN stands for False Negative and FP stands for False Positive.

The performance of the proposed method is also tested for various noises as in Fig. 2 illustrates the segmentation accuracy. It is observed that, the proposed method has better segmentation accuracy compared to SVM and AAM. The computation time for various medical images with and without noise levels are analyzed and listed in Equations:

$$\text{Sensitivity}\frac{a}{a+c} = 50.00\ \%; 95\%\ \text{CI}: 12.42 - 87.58\ \%$$

$$\text{Specificity}\frac{d}{b+d} = 46.15\ \%; 95\%\ \text{CI}: 19.33 - 74.78\ \%$$

$$\text{PositiveLikelihood Ratio}\ \frac{\text{Sensitivity}}{100 - \text{Specificity}}$$
$$= 0.93; 95\%\ \text{CI}: 0.36\text{-}2.39$$

$$\text{NegativeLikelihoodRatio}\frac{100 - \text{Sensitivity}}{\text{Specificity}}$$
$$= 1.0895\%\ \text{CI}: 0.40\text{-}2.92$$

$$\text{Disease prevalence}\frac{a + c}{a + b + c + d}$$
$$= 31.58\ \%(\times)95\%\ \text{CI}: 12.65 - 56.54\%$$

$$\text{PositivePredictiveValue}\frac{a}{a+b}$$
$$= 30.00\ \%(\times)95\%\ \text{CI}: 7.03 - 65.16\%$$

$$\text{NegativePredictive}\ \ d = 66.67\%(\times)95\%\ \text{CI}: 30.07 - 92.12\%$$

Table 1:Simulation output for multi modality image analysis

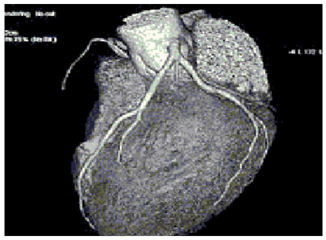
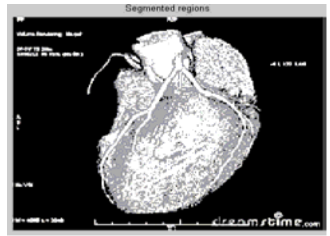
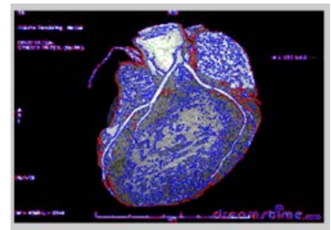
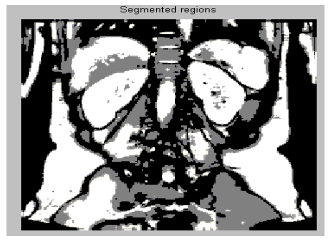
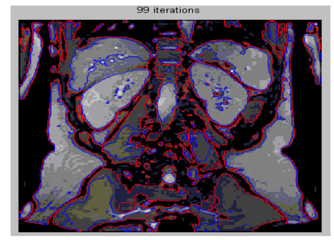
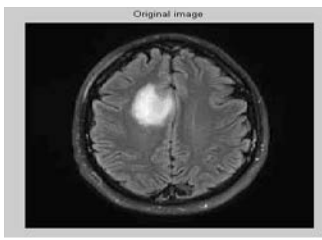
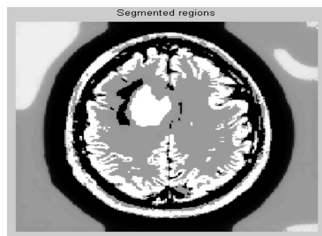
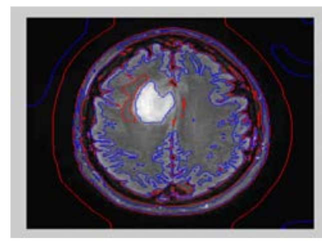
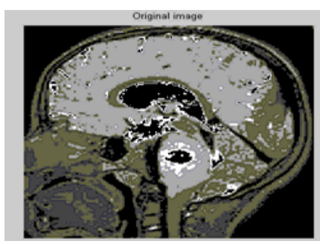
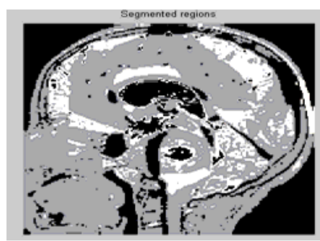
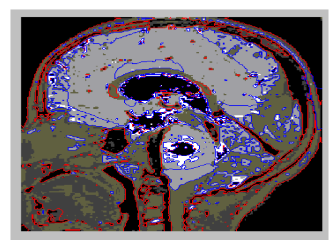
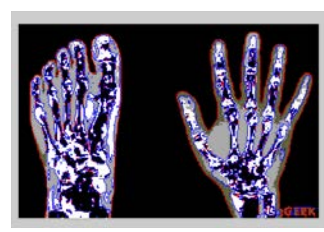
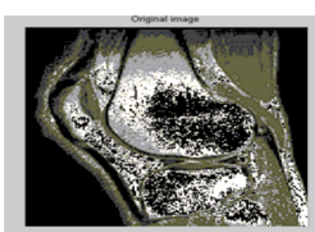
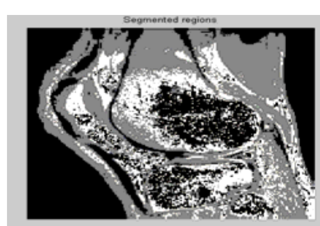
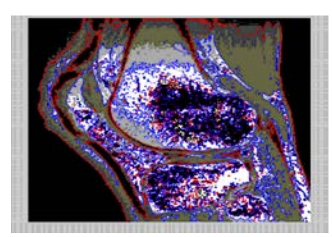
Multi modality images	Original image	Segmented image	GVF optimized image
Heart image			
Lungs image			
Brain image			
Skull image			
X Ray image			
Knee image			

Table. 2: Comparison of computational time

Types of images (MRI Images CT scan images X-Ray images)	Computation time		
	SVM (Support Vector Machine)	AAM (Gradient vector flow)	GVF (Active appearance model)
Original images (s)	250	236	215
Images with noise (s) (Gaussian)	340	310	285

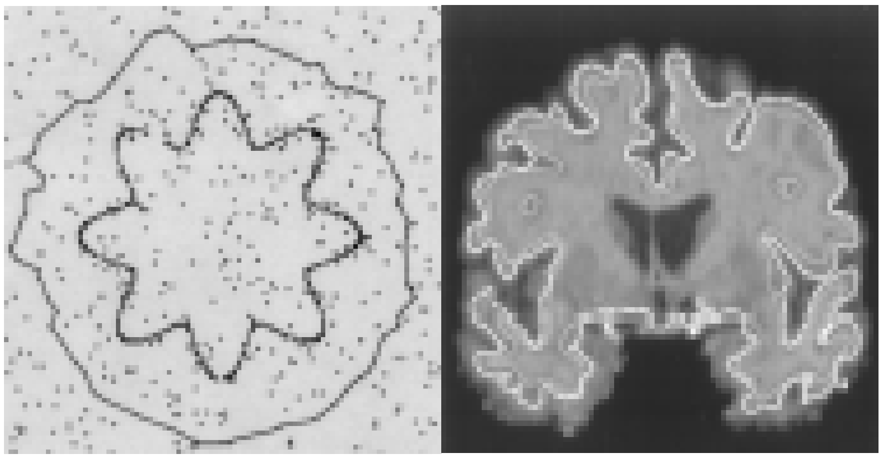


Fig. 2: Comparison of segmentation accuracy

CONCLUSION

Bio medical image is a computer visual representation of the interior of the body for clinical and medical analysis. Early detection and classification of brain diseases is very crucial in clinical to cure the patient. In this study, the gradient vector flow field and its characteristic of contour position are analyzed. The performance of GVF is measured in terms of sensitivity and accuracy with the parameters of true positive, true negative, false negative and false positive. This method improves the accuracy, computation time and reduces the noise and its timing complexity.

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