

## Automatic Brain Tumors Segmentation of MR Images using Fluid Vector Flow and Support Vector Machine

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**Abstract:** Manual segmentation of brain tumors by medical practitioners is a time consuming task and has inability to assist in accurate diagnosis. Several automatic methods have been developed to overcome these issues. But Automatic MRI (Magnetic Resonance Imaging) brain tumor segmentation is a complicated task due to the variance and intricacy of tumors; to over by this problem we have developed a new method for automatic classification of brain tumor. In the proposed method the MRI Brain image classification of tumors is done based on Fluid vector flow and support vector machine classifier. In this method Fluid Vector Flow is utilized for segmentation of two dimensional brain tumor MR images to extract the tumor and that tumor can be projected into the three dimensional plane to analyze the depth of the tumor. Finally, Support vector machine classifier is utilized to perform two functions. The first is to differentiate between normal and abnormal. The second function is to classify the type of abnormality in benign or malignant tumor.

**Keywords:** Active contour models, fluid vector flow, Gaussian filter, Magnetic Resonance Imaging (MRI), Support Vector Machine (SVM)

### INTRODUCTION

Medical imaging constitutes various modalities to create images of the human body such as X-RAY, Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Ultrasound. X-RAY, invented by Winhelm in 1895 is the oldest source of electromagnetic radiation used for imaging having wavelength in the range of 0.01 to 10 nm. It emits high radiation to create images of the human body thereby causing side effects such as cancer and eye cataract. Then Computed Tomography (CT) came into existence. CT scan utilizes X-ray to produce two dimensional images of the structures in the thin section of the body. CT produces a volume of data which can be manipulated through a process known as windowing, in order to demonstrate various bodily structures based on their ability to block the X-ray beam. Although most common in medicine, CT is also used in other fields such as nondestructive materials testing.

Since it has a greater ionizing radiation dose burden, repeated scans must be limited to avoid health effects. MRI or Magnetic Resonance Imaging invented in 1970 is a popular method in medical imaging. A magnetic resonance imaging instrument that is MRI scanner, or Nuclear Magnetic Resonance (NMR)

imaging scanner as it was originally known, uses powerful magnets to polarise and excite hydrogen nuclei (single proton) in water molecules in human tissue, producing a detectable signal which is spatially encoded, resulting in images of the body (Logeswari and Karnan, 2010).

MRI uses three electromagnetic fields, a very strong static magnetic field to polarize the hydrogen nuclei, called the static field, a weaker time-varying field for spatial encoding, called the gradient field and a weak radio-frequency field for manipulation of the hydrogen nuclei to produce measurable signals, collected through a Radio Frequency antenna. MRI traditionally creates a two dimensional image of a thin "slice" of the body and is therefore considered a homographic imaging technique. MRI clearly differentiates soft tissues and it produces no side effects like CT and X-rays. One of the challenging tasks in medical imaging is the segmentation of tumors by physicians. A tumor is a mass of tissue that grows as out of control of the normal forces that regulate growth. There are various types of tumors of which brain tumor is the cause of one quarter of all cancer deaths. The complex brain tumors can be separated into two categories depending on tumor origin as primary and metastatic tumors. Primary brain tumors are tumors that arise from cells in the brain or from the covering of the

brain. A secondary or metastatic brain tumor occurs when cancer cells spread to the brain from a primary cancer in another part of the body. Several automatic tumor segmentation methods which are rapid and time preserving have been developed (Xianghua and Majid, 2004).

Active Contour Models or Snakes are effective tools for segmentation. There are two types of active contour models, parametric and level set active contour models. Parametric active contour models are able to extract a single object and are often faster than level set models. Parametric snakes have two weaknesses; the capture range is limited and inability to capture acute concave shapes (Shan *et al.*, 2005; Nicolas *et al.*, 1999). Level set active contour models are able to capture multiple objects and complex geometries and are slower than parametric methods. In the presence of noise level set snakes capture multiple false objects. In the existing work parametric active contour models such as Gradient Vector Flow (GVF), Boundary Vector Flow (BVF) and Fluid Vector Flow (FVF) and level set active contour models such as Magnetostatic Active Contour model (MAC) were used for extracting the boundary of the brain tumor but these models differ by their capture range and their ability to capture acute concavities. FVF demonstrated improvements over other techniques with its large capture range and better convergence for concavities (Chenyang *et al.*, 1998; Kass *et al.*, 1998; Tao *et al.*, 2009). It is proposed to utilize Fluid Vector Flow for extracting the tumor in brain MR image and projection of extracted tumor into the three dimensional space i.e., 3D visualization to analyze the depth of the tumor.

The main contributions of our proposed technique are:

- Pre-processing the input MR images using Gaussian filter
- Tumor regions are identified using region props algorithm and segmented the region using morphological operation
- Feature extraction for the region is done with the help of Fluid Vector flow
- Selected features are input to Support Vector Machine (SVM) neural network for training, finally classify the tumor and non-tumor images
- Used evaluation matrices parameters of sensitivity, specificity and accuracy to evaluate the performance of the proposed technique of tumor detection

## LITERATURE REVIEW

Lots of researches have been performed for the segmentation of normal and abnormal tissues in MRI brain images. Some of the recent related works

regarding the segmentation of brain tissues are reviewed in this section.

Kekre *et al.* (2010) have proposed a vector quantization segmentation technique to identify cancerous mass from MRI images. In order to improve the radiologist's diagnostic performance, Computer-Aided Diagnosis (CAD) scheme has been introduced to enhance the recognition of primary signatures of this disease: masses and micro calcifications. As well, a template-based framework for multi-object segmentation of deep brain structures (caudate nucleus, putamen and thalamus) in medical brain images has been presented by Jue and Albert Chung (2009). This framework combines the information of edge features, region statistics and inter-structure constraints for identifying and locating all target brain structures. The multi-object template has been structured in the form of a hierarchical Markov Dependence Tree (MDT) and manifold objects have been successfully matched to a target image via a top-to-down optimization approach. The final segmentation has been achieved through refinement by a B-spline based non-rigid registration between the exemplar image and target image. The approach necessitates only one example as training data. The technique has been validated using a publicly available T1-weighted MRI database with expert-segmented brain structures and obtained satisfactory results as 0.80 Dice score for the caudate nuclei, 0.81 Dice score for the putamen and 0.84 Dice score for the thalamus on average.

In order to enhance the performance of automated image segmentation, especially in the field of brain tissue segmentation from 3D MRI towards classical image deterioration including the noise and bias field artifacts that arise in the MRI acquisition process, Caldairou *et al.* (2009) have proposed to integrate into the FCM segmentation methodology concepts stimulated by the Non-Local (NL) framework. The major algorithmic contributions of this study were the definition of an NL data term and an NL regularization term to effectively handle the intensity inhomogeneity and noise in the data. Then, the resulting energy formulation was built into an NL/FCM brain tissue segmentation algorithm. Experiments carried out on both the synthetic and real MRI data, leading to the classification of brain tissues into grey-matter, white matter and cerebrospinal fluid, have shown a substantial enhancement in performance in the case of higher noise levels, when compared to a range of standard algorithms.

## PROPOSED METHODOLOGY

The Objective is to segment the brain tumor using Fluid Vector Flow (FVF) and three dimensional visualization of tumor. The contour evolves to capture

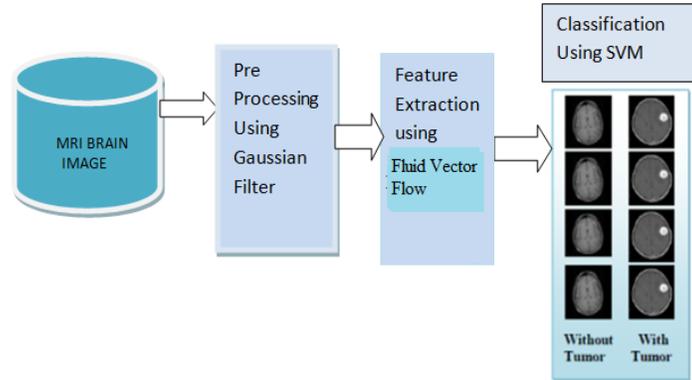


Fig. 1: Proposed system flow diagram

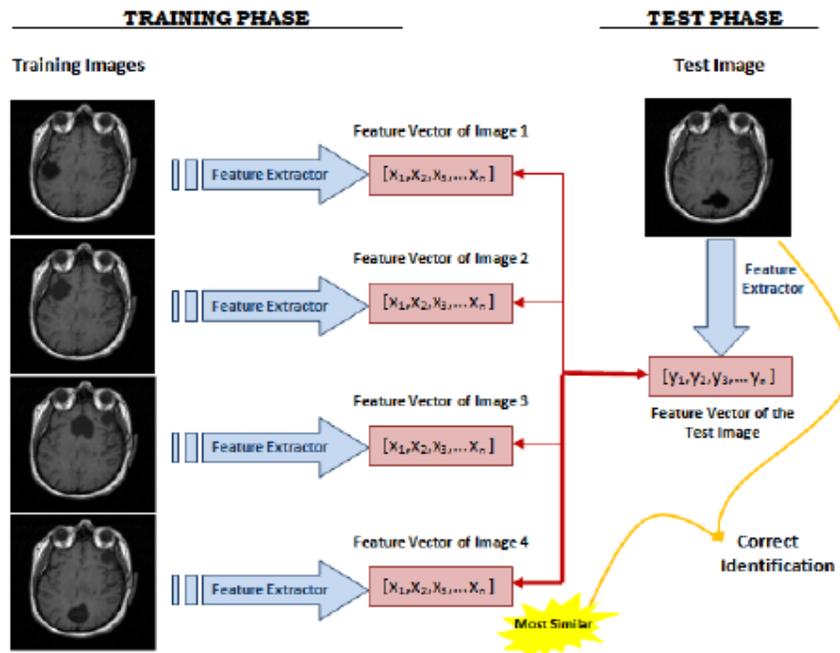


Fig. 2: Schematic diagram of MRI image recognizer

the target object i.e., the brain tumor. The methods used are preprocessing, binary boundary map generation, vector flow initialization, FVF and Depth Analysis. Figure 1 shows the flow diagram of the proposed method which starts with smoothing the input image using a Gaussian smoothing filter and edge finding using a gradient operator. Then binary boundary map is generated and vector flow is initiated and FVF is computed iteratively until the object i.e., the tumor is extracted. Then the extracted tumor is projected onto the three dimensional plane for analyzing the depth or volume of the tumor.

**Pre-processing:** It is the first step in our proposed technique. The purpose of these steps is basically to remove the noise and improve the image quality to get more surety and ease in detecting the tumor. Here, the input image is passed through a Gaussian filter to remove the noise in order to obtain a better image. Also, improves the image quality. The proposed method Schematic Diagram of MRI Image Recognizer is shown in Fig. 2.

**Gaussian filter:** The Gaussian blur (Haddad and Akansu, 1991) is a type of image-blurring filter that uses a Gaussian function for calculating the

transformation to apply to each pixel in the image. Each pixel's new value is set to a weighted average of that pixel's neighborhood. The original pixel's value receives the heaviest weight (having the highest Gaussian value) and neighboring pixels receive smaller weights as their distance to the original pixel increases. This results in a blur that preserves boundaries and edges better than other, more uniform blurring filters; see also scale-space implementation. The input image undergoes smoothing using Gaussian smoothing filter for elimination of noise. Gaussian filter is a linear spatial filter which is used for reducing the high frequency components of an image as a result it smooths the edges of the input image. Gaussian Smoothing is performed by convolving the input image with the Gaussian function i.e.:

$$G_{\sigma}(x, y) * I(x, y)$$

$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

where  $I(x, y)$  is the input image,  $G_{\sigma}(x, y)$  is Gaussian smoothing filter with standard deviation  $\sigma$ ,  $x$  and  $y$  are the spatial coordinates and  $*$  is the convolution operator.

Gradient operator is then applied to the smoothed image to find edges in the image which have been suppressed by the Gaussian filter i.e.:

$$\nabla(G_{\sigma}(x, y) * I(x, y))$$

where  $\nabla$  is the gradient operator which calculates the directional changes in intensity values.

**Binary boundary map generation:** The boundary map is defined as:

$$MB(x, y) = \nabla(-G_{\sigma}(x, y) * I(x, y))$$

where,

$G_{\sigma}(x, y)$  = The Gaussian smoothing filter with standard deviation  $\sigma$

$*$  = The convolution operator

$\nabla$  = The gradient operator

The normalized boundary map is defined as:

$$M_{NB}(x, y) = \frac{M_B(x, y) - \min(M_B(x, y))}{\max(M_B(x, y)) - \min(M_B(x, y))}$$

Similar to BVF a threshold  $T \in [0, 1]$  is applied to generate the binary boundary map:

$$M_{BB}(x, y) = 1 \text{ if } M_{NM}(x, y) > T \\ \text{else } 0$$

The choice of suitable threshold value varies depending on the intensity distribution and contrast associated with the set of images being analyzed. For the brain MR images a threshold of 0.1 is used to achieve object continuity and for extracting the low intensity region. The extracted boundary provides an envelope to ensure that final convergence is not out of bound.

**Segmentation:** Magnetic Resonance Imaging (MRI) is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. The goal of Magnetic Resonance (MR) image segmentation is to accurately identify the principal tissue structures in these image volumes. However in MRI images, the amount of data is far too much for manual interpretation and analysis and this has been one of the biggest problems in the effective use of MRI. In the specific case of brain MRI, the problem of segmentation is particularly critical for diagnosis and treatment purposes.

It is necessary to develop algorithms to obtain robust image segmentation such that the following may be observed:

- Automatic and semi-automatic delineation of areas to be treated to radio surgery.
- Delineation of tumors before and after surgical or radio-surgical intervention.
- **Tissue classification:** Volumes of White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF), Skull, Scalp and abnormal tissues.

#### FEATURE EXTRACTION USING FLUID VECTOR FLOW (FVF)

In our proposed method, Fluid Vector Flow based image feature retrieval scheme is used. The FVF feature extraction process is a two step process which consists of:

- Vector flow Initialization
- FVF computation and contour extraction

**Vector flow initialization:** The contour must be initialized to initialize the external force field. The initial contour can be inside, outside or

overlapping the target objects. FVF is insensitive to initialization by taking advantage of the binary boundary map. Contour C can be represented as:

$$c(i) = \{(x_i, y_i)\}; i \in [0, 1, \dots, P-1]$$

where, P is the number of points on the contour. An external energy function is defined as:

$$E_e(x, y) = \chi(f_x + \delta \cos \theta, f_y + \delta \sin \theta)$$

When  $M_{BB}(x, y) = 0$ ,  $E_e(x, y)$  holds the first value in (8), otherwise holds zero.

where  $\chi$  is a normalization operator,  $\delta = \pm 1$  (controls the inward or outward direction when the contour is “outside” or “inside”):

$$(f_x, f_y) = \chi(\nabla I(x, y)) \text{ and } \theta \in [0, 2\pi]$$

**FVF computation and contour extraction:** A trace method is applied to the binary boundary map to get a list of control points. The control points are used to generate the external force fields. FVF has 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 external force field dynamically. A parameter  $\delta$  is used to manage the selection of control point. The method selects 1 out of  $\delta$  control points to achieve better time efficiency. Once the control point moves to its new location it generates new external force field for further evolution of contour until convergence is achieved. FVF computation is iteratively performed to extract the tumor.

**Final classification:** After feature extraction process, In-order to detect the presence of the tumor in the input MRI image, we perform the final classification step. Here we use the Support Vector Machine classifier to classify the image into tumorous or not. In 1995, Support Vector Machine (SVM) has been developed, which is an effective supervised classifier and accurate learning. Technique it is derived from the statistical theory invented by Vapnik (1982).

It produces successful classification results in several application domains, for e.g., medical diagnosis (Zhang *et al.*, 2006). SVM follows the structural risk minimization principle from the statistical learning theory. Its kernel is to control the practical risk and

classification capacity in order to broaden the margin between the classes and reduce the true costs (Zhang and Liu, 2004). A support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high.

SVM has also been applied on different real world problems such as face recognition, text categorization, cancer diagnosis, glaucoma diagnosis, microarray gene expression data analysis. Proposed system used SVM for binary classification of brain MR image as normal or tumor affected. SVM basically tries to divide the given data into decision surface. Decision surface is a hyper plane which divides the data into two classes. Training points are the supporting vector which defines the hyper plane. The kernel function  $H(x, x_1)$  is defined by:

Polynomial kernels are:

$$H(x, x^1) = (x^p x^q + 1)^d$$

where d is an integer.

RBF kernel is:

$$H(x, x^q) = \exp(-\gamma \|x - x^q\|^2)$$

where  $\gamma$  is positive parameter is slope control.

## EXPERIMENTAL RESULTS

This section describes the experimental results of our proposed Segmentation technique using brain MRI images with and without tumors. Our proposed approach is implemented in MATLAB (MATLAB version 7.10). The proposed system has been tested on dataset of real brain MR images consisting of normal and tumorous brain images. Figure 3 shows some of the test images collected from publicly available sources.

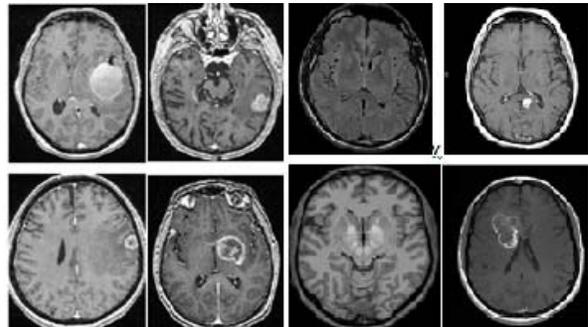


Fig. 3: MRI image dataset

Table 1: Various results of experimentations

Various criteria	Different methods		
	FFNN+SVM	RBF+SVM	FVF+SVM
Specificity	1.0	0.8	1.0
Sensitivity	0.6	0.7	0.8
Accuracy	0.6	0.8	0.9

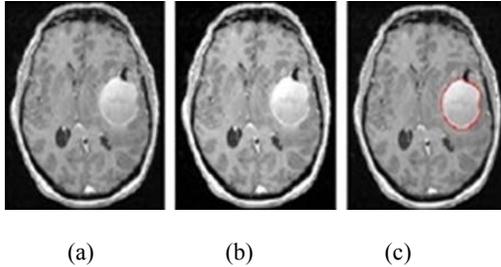


Fig. 4: (a) Original image, (b) filtered image, (c) segmented image

Table 1 shows the results of all experimentations. We first perform classification of the dataset. Once the classification is done, the malignant brain images are further segmented for extraction of tumor region from these brain MR images. Performance of each classifier is measure in terms of sensitivity, Specificity and Accuracy (Wen *et al.*, 2010). The obtained experimental results from the proposed technique are given in Fig. 4.

Sensitivity is a measure which determines the probability of the results that are true positive such that person has the tumor. Specificity is a measure which determines the probability of the results that are true negative such that person does not have the tumor. Accuracy is a measure which determines the probability that how much results are accurately classified:

$$Sensitivity = TP / (TP + FN)$$

$$Specificity = TN / (TN + FP)$$

$$Accuracy = (TN + TP) / (TN + TP + FN + FP)$$

where,

- TP : True Positive
- TN : True Negative
- FN : False Negative
- FP : False Positive

Figure 4 shows the competitive charts of different methods.

**Comparative analysis:** We have compared our proposed tumor detection technique GLCM+SVM to other neural network techniques. The neural networks we have utilized for comparative analysis are

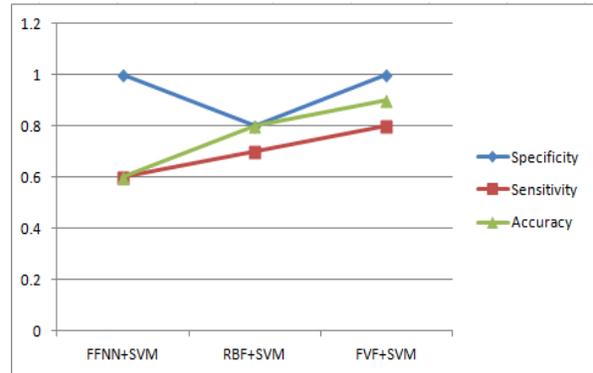


Fig. 5: Comparative analysis graph

Artificial Neural Network (ANN) and Radial Basics Function (RBF). The performance analysis has been made by plotting the graphs of evaluation metrics such as sensitivity, specificity and the accuracy. By analyzing the plotted graph, the performance of the proposed technique has significantly improved the tumor detection compared with Artificial Neural Network (ANN). The evaluation graphs of the sensitivity, specificity and the accuracy graph are shown in Fig. 5. The accuracy level proved that the proposed algorithm graph is good in detecting the tumors in the brain MRI images.

## CONCLUSION

A parametric Fluid Vector Flow active contour model is utilized for automatic segmentation of tumor in brain MR images and the segmented tumor is visualized in three dimensions for depth analysis. Since a tumor doesn't exhibits any prior shape, delineating the tumor accurately is a difficult task. FVF is utilized for segmentation because it can deform in all directions for capturing the tumor. It also addresses the issues of limited capture range and the inability to extract complex contours with acute concavities. Segmentation aids in visualization of area of tumor. Volumetric projection is proposed to analyze the third dimension i.e., the volume or depth of the tumor. This automatic method for brain tumor segmentation and three dimensional visualization will help physicians in accurate diagnosis.

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