Brain Ischemic Stroke Segmentation: A Survey

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Abstract

In this survey paper a comprehensive survey of segmentation techniques used for localizing brain stroke area (differentiating it with normal region of brain) has been presented. In recent times, automated systems are preferred over manual and semi automated systems. Segmentation or localization is not a challenge, challenge lies behind producing an automated, reproducible and clinically accepted method which works well in case of abnormalities too and can be used for further processing like computing volume, growth prediction and treatment etc. As in today's time there is no place for erroneous interpretations but large number of stroke cases overburden the radiologists and may result in wrong analysis. So, an efficient automated segmentation method is need of an hour and is preferred over conventional systems. The most relevant methods whether manual, semi automated or automated for segmentation are discussed. So, it sets up a picture where there is scope of improvement to reach a goal.

Key Words: Segmentation, MRI, and Brain Ischemic Stroke.

1. INTRODUCTION

In medical domain, brain stroke or just stroke is a condition in which cells in certain portion of brain die due to lack of oxygen supply. The scarcity of oxygen in certain portion of brain may arise due to obstruction in or rupture of an artery that carries oxygen rich blood to that part of the brain [1]. Stroke is a serious medical emergency, and may cause paralysis, memory loss or even death. With the increasing level of stress and hypertension in daily life, the brain strokes have become a common problem. According to the surveys, [2, 3] worldwide about 16 million people suffer from acute stroke every year, and 5 million die due to it. The alarming state of the problem can be fathomed from the fact that stoke has become the second leading cause of death and fourth leading cause of disability worldwide [2]. Out of all stroke victims only 10 percent recover almost completely, 25 percent recover with minor impairments, 40 percent needs special care, 10 percent require much care in some clinic and 15 percent die shortly after the stroke [2].

Stroke is majorly of two types ischemic and hemorrhagic. Ischemic stroke occurs when there is any blockage in blood vessel due to which blood supply is to part of brain only. There are four general reasons behind this:- Thrombosis, Embolism, Systemic hypoperfusion and Venous thrombosis. In hemorrhagic stroke tissues get ruptures due to hematoma expansion and pressure results in infarction. Recent observations have shown that 82 - 92 percent cases are of ischemic stroke [5]. This going on increasing rate does not allow radiologists to segment manually which is tedious, time consuming and inaccurate task.

Images are used to capture some details. How minutely the details are captured, depends on the imaging technique. Brain scanning is required to observe whether internal functioning is working correctly or not, without any surgery. Commonly used imaging modalities for brain are, CT Scan and MRI. Among both, MRI is better due to its efficiency of producing contrast between gray scales and it does not cause harmful ionizing radiations like of CT [31]. So, MR imaging is preferred over CT scan and many of the segmentation techniques have been applied on it for segmenting region of interest (stroke area).

Ischemic stroke segmentation is separating hyperintensed region from brain image i.e. to segment infarcted piece from normal gray matter, white matter and CSF. Trends have shown, it being performed by experts, which is a critical task. Although assessment is performed precisely and with accuracy but this often gets difficult for them and will never be 100% accurate. Moreover, radiologist's mental health, if not stable, can result adversely. So, some automated stroke segmentation method is required. Formally it can be defined as segmenting a brain image in two groups R1 and R2 if there is a stroke region.

$$\cup_{i=1}^{2} R_i = R \quad (1)$$

$$R_1 \cap R_2 = \emptyset \quad (2)$$

$$(\forall_i = 1,2,\ldots)\ P(R_i) = TRUE \quad (3)$$

$$P(R_1 \cup R_2) = FALSE \quad (4)$$

Where P is uniformity predicate followed by all elements in a set. ROI generated will be a closed region.

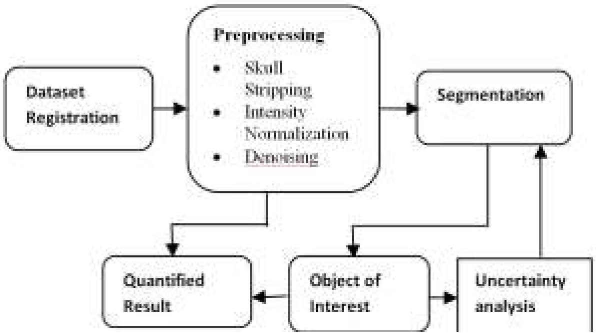

Fig -1: Brain Ischemic Stroke Segmentation Approach

Figure1. shows basic approach which is required to be followed in all kinds of segmentation methods used. Medically, ischemic stroke region is of great importance as it provides concerned information like which region of brain and by how much percent it is affected and much more clinically required features. Extracting useful information from multidimensional images is a vital task in medical images segmentation. Thus, accuracy of clinical information depends upon locating region precisely, which will help for treatment by formulating right methodology as soon as it is diagnosed and region will be calculated [6]. Many researchers from medical imaging and artificial intelligence field contributed in segmentation by proposing various approaches which are discussed briefly and are grouped under various well known, major segmentation methods. Work is divided in 6 sections. Section 2 introduces about thresholding methods, in section 3 region based methods are discussed, section 4 is about pixel classification methods, in section 5 Deformable model based segmentation techniques are presented. Summary of the discussed segmentation methods is in section 6.

2. THRESHOLDING BASED METHODS

Threshold based method is the most primitive one which is purely based on change in intensity levels for extracting region of interest. Threshold value plays a key role and is usually set interactively or by analyzing histogram of an image. Thresholding can be defined as an operation that involves tests against the function T,

$$T = T[(\vec{x}), p(\vec{x}), f(\vec{x})]$$

Where x is the spatial position of image point, p(x) is a local neighborhood property, f(x) is gray level intensity.

It represents a gray scale image in a binary scale or in k bits scale (multilevel) and are applied on contrasting images like where bright object placed on dark object.

Threshold values can either be local or global. There can be multiple individual thresholds or multilevel thresholding segmentation. Global thresholding is the oldest and the simplest process amongst all methods but it cannot justify all variations in an image as threshold value is determined by considering properties of whole image. There can be variations within the object which can be diagnosed through local threshold method. This is an adaptive method which is used when threshold value is not determined from a part of an image.

Otsu's method is used to find optimal threshold value by focusing on maximizing gray level variance and relieves from problem of determining normal distribution parameters. Thus it is widely acceptable threshold determining method. But single threshold value can never be sufficient in segmenting medical images. So, Kalvathi P. proposed [8] brain mr images segmentation into GM, WM and CSF method using multiple Otsu's thresholding technique by reading every slice and computing threshold again for every slice.

Hybrid threshold based method considers features of both local and global threshold and is discussed [9] for brain lesions (just like stroke) in which image was divided into small regions but optimal threshold was decided by comparing normal and lesion region considering the fact that infarcted pixels are brighter than normal ones. It also used contrast enhancement technique and proves gamma-law transformation is better than contrast stretching. But this approach cannot be used as a standard because better methods with clinical acceptance and reproducible segmentation are required. It [10] compares segmentation results of adaptive threshold method [9] with GLCM method and found that GLCM is better method with negligible but significant difference due to statistical fluctuations in ROI. Sometimes threshold method comes into picture with some other methods as proposed for developing methods that can automatically enhance contrast of ischemic lesions.

Threshold based methods are widely used in 2D MR images. But Yi Wang et al. [4] showed its application in segmenting 3D images using entropy based multi-threshold method and along with it, improved-immuno genetic algorithm was used. IIGA is stable and gives accurate threshold values.

Thresholding plays with region by including background unwanted pixels and ignoring required regional pixels and situation gets worse in case of noise. It is a well defined method for images with homogeneous intensity and contrasting region of interest. Its results are questionable with large statistical variations. Hence cannot be used for defining an automatic segmentation method alone.

3. REGION-BASED METHODS

As the name specifies segmentation is done by forming regions according to some predefined criterion [13]. Region growing is generally of two types 1) Region merging 2) Split and merge. Region growing is a basic connected region yielding method which starts with at least one seed point and spreads like roots of tree by considering its neighboring pixels for uniformity test [12]. Those pixels which pass this test get merge with region. In split and merge technique entire image is divided into quadrants i.e. small regions unless and until a sub region is formed which contains all homogeneous pixels. If pixels of adjacent regions are compatible, they can be merged. It is very easy to understand. Consider an image i and divide it into n sub parts such that

i) on putting all of them together once again we get an original image and

ii) ii) none of the region should overlap with each other.

$$I = \cup s_j \tag{6}$$

$$s_j \cap s_k = 0 \forall_{j,k}\ 1,2,3, \ldots\ldots n \tag{7}$$

$$l(s_j) = \text{true} \forall_j\ 1,2,3, \ldots\ldots n \tag{8}$$

$$l(s_j \cup s_k) = \text{false} \forall_{j,k}\ 1,2,3, \ldots\ldots n, j \neq k \tag{9}$$

Logical predicate l () specifies all the properties a region must have.

Such a method was used in stroke lesion segmentation in connection to edge detection [13] in which it showed better results for T2 and FLAIR imaging rather than DWI which is a better imaging technique but with significant 4.1% error. Such segmentation processes need human interference to indicate seed point [14, 15, 17} and then the region grows till the condition is satisfied. This gives a very simple and basic method of segmentation with less computations and still very effective. Lilian C.et al [15] also proposed a semi automated method for segmentation of core region in ischemic stroke in CT images but in this method a different criterion of mean and standard deviation was chosen to select pixels from 8-connectivity and gave better results than being solely dependent on intensity values, reason behind this was intensity of ROI varies sharply and segments get overlap. Generally in all the methods one has to go through number of slices, but to avoid this a sketch based interactive method was proposed by H. L. J. Chen et al.[17] which focus on ease of user(radiologist) using seed point method. Thus it's easy for some non technical person but results are not evaluated on some metrics which could prove worth of the method.

By taking out simple features on region based parameters from basic split and merge based region growing algorithm an automated technique can be prepared without manual interference.

Watershed method is a topography based method like a water drop flowing downhill after falling somewhere on landscape during rain till it reaches another water body like valley which is enclosed by catchment basin. Each point can belong to a single catchment basin which is differentiated from adjacent ones by topographical lines. Dams are built where water from different basins convene i.e. to define a boundary of ROI, this algorithm is interested in watershed lines [18]. Thus, landscape is partitioned on areas where dams are built called watersheds.

C. Amutha Devi used this method for extracting features along with gabor filtering method for classifying brain stroke region [18]. Practical use of this method has been seen more in case of tumor segmentation [19, 20] but less in stroke lesions.

It works on getting pixels with maximum gradient intensities and local minima. Hence, it leads to over segmentation and it requires additional processing to overcome this disadvantage and there are methods which can be used as pre-processing or post-processing steps with this model [21].

4. PIXEL CLASSIFICATION METHODS

Pixel is a fundamental unit of an image which represents the basic properties of an image like color, texture and brightness. Pixel based classification means forming clusters based on predefined criterions like spectral characteristics such as mean, standard deviation, and co-variance etc.

Clustering techniques are mainly of two types unsupervised and supervised. In unsupervised means pixels categorization is an automatic procedure according to pre-defined statistical criteria and number of classes are not fixed. Onlyrelabeling is done by analysts to form information classes. Unsupervised methods consider properties like texture and intensity but not anatomical and have given efficient results in cases like finding different regions in tumor [22]. Fuzzy C Means, K-means, Markov Random fields are unsupervised clustering methods. Supervised methods use manually segmented labeled training data to classify an image into mutually exclusive segmented regions. In this case number of classes is decided by an operator based on MR data being examined but training data has to be chosen carefully as it decides classification result [12]. Bayes and ANN are supervised methods.

The FCM clustering algorithm was introduced by Bezdek [23] which classifies voxels in an image like MRI into pre-specified number of clusters based on voxels intensities. Likeliness of every voxel with each cluster is measured by fuzzy membership function U which is based on intensity difference between voxel and center cluster [24] where N represents number of voxels and C represents number of clusters, xj (j=1.....N) represents voxel intensity and vi(i=1..C) refers to cluster centre i.e. an approximation of average intensity in this cluster, d2(xj ,vi) measures similarity between xj and vi by calculating their Euclidean distance. m $\in (1, \infty)$ is a weighting exponent on each fuzzy membership, which controls the degree of fuzziness [23].

Shan Shen et al. proposed a method which was based on conventional FCM and was for uni-spectral MRI scan [25] and gave comparable results to those performed on multi-spectral MRI scans. Main idea behind it was the intensity based segmentation of voxels and the tissue distribution (spatial location based) should be inconsistent in the lesions area but this approach failed in case of acute lesions and misinterprets ventricles as lesions. Umut Ozertem et al. proposed a method [28] in which infarcted region was determined by evaluating a feature map for each pixel as root mean square intensity with a square neighborhood around a pixel and then it was classified using any clustering algorithm.

FCM does not consider neighboring properties which may leads to noise and is an iterative time consuming algorithm but always converge towards boundaries of ROI.

Iterative Self Organizing Data Analysis (ISODATA) technique is an unsupervised classification technique, similar to the k-means algorithm with a difference that the ISODATA algorithm allows for different number of clusters while the k-means allow only pre-defined number of clusters. Both k-means and ISODATA are iterative procedures in which cluster means is calculated again and again based on pixels in a cluster and this mean value pixel is used to classify pixels to closest cluster. Automatic ISODATA technique based on mahalanobis distance was used to track acute ischemic stroke fats in rats [26]. Besides being easy approaches both of these techniques have rarely been used in ischemic stroke segmentation.

ISODATA is sensitive to noise, image artifacts, variances of clusters and is fundamentally dependent on normality assumption for distribution of clustered data which makes it unsuitable to be used in this case [27].

MRF is a clustering based method which considers pixels spatial information assuming if one voxel is strongly infarcted it is likely that neighboring voxel will also be infracted [12].

Markov model based method was proposed [39] using digital atlas of brain blood supply territories assuming lesion intensity was different from normal tissue intensity and selecting parameters carefully. Parameters need to be selected carefully in case of MRF.

Artificial Neural Network is a supervised clustering technique which consists of multiple nodes arranged in layers. Input layer is to receive input from real world. There are multiple hidden layers in which neurons are interconnected and output from one hidden neuron goes to another. There is output layer which outputs result which can be any character or an image. It is trained for the values of parameters to be used for mathematical operators to minimize error during output [12].

H. Bagher-Ebadian et al. proposed an ANN method [29] for predicting extent of ischemic infarction to estimate its recovery which used four image sets(T1WI, T2WI, DWI and PDWI) and considered 3 month T2WI as gold standard. This can be considered as a great tool as it can be performed in real time and is robust method to evaluate stroke in progress. Shanthi et al [33] demonstrated ANN for predicting the Thrombi-embolic stroke disease with overall accuracy of 88.5%. ANN can also be used for classifying image as stroke or non-stroke. For this an experiment showed [30] that better results were obtained on extracting 80-120 root mean squares based features.

Main idea behind segmenting infarcted region sharply in scanned images is to get its volume, but on calculating, volume varies with different scanning techniques. A semi automatic method [30] was presented which calculated mismatch in infarcted volume by different scanning techniques and gave different reasons for it like image quality and parameter values etc.

ANN is complex method due to its large structure.

5. DEFORMABLE MODEL BASED TECHNIQUES

Deformable models are curves or surfaces in case of 2D images and hyper-surfaces in case of higher dimensions like 3D images. Key work behind Deformable models is determining propagating interface by local, global and independent properties which will propagate under speed function. Image features depend on type of image like in MRI, gradients are used for edges information. There are two basic types of deformable models Parametric Deformable model and Geometric Deformable Model.

Parametric deformable models, commonly known as active contour models or snakes and were first introduced in 1988,by Kass et al. [32] They deform with control of two different internal and external forces to define sharp ROI boundary. Internal forces are defined within the curve or surface to maintain shape smoothness of model whereas external forces are based on image features to take the model towards desired position. Energy is calculated for all points in neighborhood of vi.

$$E_{snake}(\mathrm{V}) = E_{int}(\mathrm{V}) + \beta E_{ext}(\mathrm{V}) \tag{10}$$

Their deformations are determined by the iterative displacement of collection of n control points in an image plane V = {v1,.,vn}, vi = (xi, yi), i = {1,.,n} towards the boundary by following energy minimization principle. Besides having contours this model can be surfaced with the control points describing 2D deformable grid for 2D image segmentation and hyper-surfaces with the control points defining three-dimensional, for the segmentation of higher-dimensional image data. A method was proposed for its efficient convergence towards weak boundary with efficient results shown in case of tumor segmentation [34]. Implicit dual snakes' approach [35] was proposed which addressed the sensitivity to local minima of general active contour models by seeking for global minima. GVF and kernel annealing based model was presented [28] to automatically segment brain and its parts and avoided problems in snake model like concavity and low capture range.

As control points are pre-defined they are fast in convergence and represents accurate description of an object. But this model works fine with single ROI. In case of multiple ROI's multiple models have to be initialized manually. Topological changes of splitting and merging has also needs to be handed manually.

Geometric Deformable Models (also referred as level sets) solve the problems associated with parametric ones. It was initially proposed by Osher and Sethian in 1988 and is based on curve evolution theory independent of parameterization. There is implicit contour formulation which transforms n dimensional curve to n+1 dimensional surface using scalar distance functions(n=1 for curves, n=2 for surfaces).

Caselles proposed a geometric method [37] which improved the initialization problem of snakes by placing an initial contour symmetrically with respect to the boundaries of interest but it will not be simple enough while dealing with irregular shaped objects like ischemic stroke. A new speed function was proposed [38] to extract curve or surface as close as possible to object boundary. Shashank Mujumdar et al. proposed a hybrid automated method using Chan-vese method [36] with high specificity of 99.90% for segmenting and calculating volume.

Level set models can segment the image more precisely than snake models but needs lot of processing effort [38].

6. SUMMARY OF BRAIN ISCHEMIC STROKE SEGMENTATION METHODS

Threshold based methods are solely based on intensity. They perform well in contrasting images but alone are not sufficient for delineating stroke boundaries. It may also consider some shadow pixels or leave out required pixels which doubt its accuracy. It fails in case of segments overlapping, due to noise or intensity variation. Thus one or multiple threshold values cannot sharply define object boundaries [9].

Region growing methods are easy way to generate connected regions but they require human interference for selecting seed point [14]. Watershed model needs some other methods as pre-processing or post-processing to avoid its shortcomings[18].

In pixel classification techniques ANN has been widely used for brain ischemic stroke segmentation. Although Fuzzy set concepts can be useful in order to define sharp boundaries but it does not consider correlation of neighboring pixels which leads to increase in noise sensitivity [25]. ISODATA and k-means are preferred to be used in case of remote sensing and are not seen for stroke segmentation [27]. Parameters have to be selected very carefully in case of MRF for efficient results [39]. ANN is complex and time consuming approach as size becomes larger due to many layers and learning time increases highly. There is a method to solve this problem proposed by Tayel [40] which focus on reducing complexity, time and space for images using ANN.

Model based segmentation is an effective approach to build automatic methods for stroke segmentation but they are computationally expensive. These can also be used to refine boundaries segmented by threshold or region based methods [28].

Advantages and disadvantages of all the methods has been presented in tabular form in table I.

Table -1: Summary table of Segmentation Methods

Segmentation Method	Advantages	Disadvantages
Threshold Based Method	Easy to use.	Limited capability to segment region sharply.
Region Based Methods		
Region Growing Watershed method	Computationally inexpensive. Ability of completing contours in multiple segmented regions	Requires human interference. Needs Pre-processing and pose-processing procedures.
Pixel Based Classification		
Fuzzy C-means Artificial Neural Network Markov Random Field	Defnes sharp boundary for segmented region. Ability to model critical dependencies. Abilty to handle complex dependencies in multispectral data.	Noise sensible. Slow learning phase. Selection of parameters is crucial
Model Based Classification		
Parametric deformable models Geometric deformable models	Efficient for building automatic methods. Can handle inhomogeneities well.	Can not handle inhomogeneities. Computationally expensive.

REFERENCES

[1] Stroke, Cerebrovascular accident, www.who.int/topics/ cerebrovascular_ accident/en

[2] Stroke Statistics, www.uhnj.org/stroke/ stats.htm

[3] Fiona C Taylor, Suresh Kumar.: Stroke in India Factsheet. South Asia Network for Chronic Disease1, IIPH Hyderabad, Public Health Foundation of India (2012).

[4] Yang. W., Yilong.N.,Yun.T., C.H.: Fast 3D Brain Multi-thresholding segmentation Based on Immuno-genetic algorithm. Prog Neurobiol, Second IEEE conference on Industrial Applications and Electronics, IEEE, 2008, pp.1882-1886.

[5] emedicine.medscape.com/article/ 1916662-overview (updated march 2013).

[6] Wong K., "Medical image Segmentation: methods and applications in functional imaging," Handb Biomed Image Anal Segmentation Models, Part B., 2, 2005, pp. 82-111.

[7] Nelly G., Eduard M., P. S., "State of the art survey on MRI Brain tumor segmentation," Magnetic Resonance Imaging, Elsevier, vol 31, 2013, pp.1426-1438.

[8] Kalvathi P., "Brain tissue segmentation in MR brain images using Multiple Otsu's thresholding technique," 8th International Conference on Computer Science & Education, IEEE, 2013, pp.639-642.

[9] N.Mohd Saad, L.S., S.A.R. Abu-Bakar,S.M., M.M.Mokji, "Brain lesion segmentation of diffusion-weighted MRI using thresholding technique," IFMBE proceedings 35, Biomed, 2011, pp.604-610.

[10] N.Mohd Saad,L.S., S.A.R. Abu-Bakar, S.M., M.M.Mokji, "Brain lesion segmentation from diffusion-weighted MRI based on adaptive thresholding and gray level co-occurrence matrix," J. Telecommunication, Electronic and Computer Engineering 3, No. 2, 2011.

[11] S. Mujumdar and J. Sivaswamy, L.T.

Kishore, R. Varma, "Auto-Windowing of ischemic stroke lesions in diffusion weighted imaging of the brain," Indian Conference on Medical Informatics and Telemedicine, IEEE, 2013.

[12] Rafael C. G., Richard E. W. Digital Image Processing, Pearson Publication, ISBN 978-81-317-2695-2, 2008.

[13] Yazid C., Asia C., Yacine K., Samith K., Asia Jaillard, M. D. and C. Garbav, "Segmentation of magnetic resonance brain images using edge and region cooperation characterization of stroke lesions," The International Arab Journal of Information Technology, vol 4, No-3, 2007.

[14] Tomasz W., Anna Fabijaska, "Brain tumor segmentation from MRI data sets using region growing approach," Perspective Technologies and Methods in MEMS Design, IEEE, 2011, pp. 185-188.

[15] Lilian C., C. B., Michael B., Hans-J-rg W., Griselda J Garrido, "Semi-automatic segmentation of core and penumbra regions in acute ischemic stroke: preliminary results," 17th International Conference on Systems, Signals and Image Processing, 2010, pp. 178-181.

[16] N. Mohd Saad, S.A.R. Abu-Bakar, Sobri Muda, M. Mokji, A.R. Abdullah, "Fully automated region growing segmentation of brain lesion in Diffusion-weighted MRI," IJCS, 39, 2012, pp. 155-164.

[17] H. L. J. Chen, F. F. Samavati, M. C. Sousa, J. R. Mitchell, "Sketch-based volumetric seeded region growing," Eurographics Workshop on Sketch-Based Interfaces and Modeling, 2006.

[18] C. Amutha Devi, S. P. Rajagopalan, "Brain stroke classification based On Multi-layer Perceptron using Watershed segmentation And Gabor filter," Journal of Theoretical and Applied Information Technology 56, No.2, 2013.

[19] Letteboer M., Niessen W., Willems P., Dam E., Viergever M., "Interactive multi-scale watershed segmentation of tumors in MR brain images," IMIVA workshop of MICCAI, 2001.

[20] Dam E., Loog M., Letteboer M., "Integrating automatic and interactive brain tumor segmentation," 17th Int Conf on Pattern Rec, IEEE, 2004.

[21] Bleau A., Leon L., "Watershed-based segmentation and region merging," ComputVis Image, vol 77, No 3, 2000.

[22] Wiselin G., Ganesan L., "Unsupervised segmentation using fuzzy logic based texture spectrum for MRI brain images," World Acad Sci Eng Technol, vol 5, 2005.

[23] J. C. Bezdek, "Pattern recognition with fuzzy object function algorithms," 1981.

[24] Samina Naz, Hammad Majeed Humayun Irshad, "Image segmentation using Fuzzy Clustering: A Survey," 6th Int. conference on Emerging Technologies, 2010.

[25] Shan S., Andre J. S., Annette Sterr, "Detection of infarct lesions from single MRI modality using inconsistency between voxel intensity and spatial location:A 3-D automatic approach," IEEE Transactions On Information Technology In Biomedicine, vol 12, 2008, pp. 532-540.

[26] Qiang S., Hongxia R., Marc F., James B., Timothy Q. Duong, "Dynamic tracking of acute ischemic tissue fates using improved unsupervised ISODATA analysis of high-resolution quantitative perfusion and diffusion data," Journal of Cerebral Blood Flow & Metabolism, vol 24, 2004, pp. 887-897.

[27] M. Koga, D. C. Reutens, P. Wright, T. Phan, R. Markus, B.Pedreira, G. Fitt, I. Lim, and G. A. Donnan, "The existence and evolution of diffusion-perfusion mismatched tissue in white and gray matter after acute stroke," Journal of the American Heart Assosciation, vol 36, 2005, pp. 2132-2137.

[28] Umut O., Andras G., Deniz Erdogmus, "Automatic brain image segmentation for evaluation of experimental ischemic stroke using Gradient vector flow and

Kernel annealing." International Joint Conference on Neural Networks, IEEE, 2007.

[29] H. Bagher-Ebadian, K. Jafari-Khouzani, P. D. Mitsias, H. Soltanian-Zadeh, M. Chopp, and J. R. Ewing, "Predicting final extent of ischemic infarction using an Artificial Neural Network analysis of multiparametric MRI in patients with stroke," International Joint Conference on Neural Networks, IEEE, 2009, pp. 229-235.

[30] Judy Rose James, Olaniyi Osuntokun, Karmen Yoder, Askiel Bruno, Evan D. Morris, "A supervised method for calculation of perfusion/diffusion mismatch volume in acute ischemic stroke", Computers in Biology and Medicine, vol 36, 2006, 1268-1287.

[31] Chelsea S. K., Amie W. Hsia., "Imaging of the Brain and Cerebral Vasculature in Patients with Suspected Stroke," Advantages and Disadvantages of CT and MRI. Current Neurology and Neuroscience Reports. 6, 2006, pp. 9-16.

[32] Kass M., Witkin A., Terzopoulos D, "Snakes: Active contour models," Int J Comput Vis, vol 1, 1988, pp.321-331.

[33] D.Shanthi, G.Sahoo, and N.Saravanan, "Designing an artificial neural network model for the prediction of thrombo-embolic stroke," International Journals of Biometric and Bioinformatics, vol 3, No 1, 2009, pp. 10-18.

[34] Wang Guoqiang, Wang Dongxue, "Segmentation of brain MRI image with GVF snake model," First International Conference on Pervasive Computing Signal Processing and Applications, IEEE, 2010, pp. 711-714.

[35] Gilson A. Giraldi, Paulo S. Rodrigues, Jasjit S. Suri, "Implicit dual snakes for medical imaging," 28th IEEE EMBS Annual Int. conference, IEEE, 2006, pp. 3025-3028.

[36] Caselles V., Catte F, Coll T., Dibos F, "A geometric model for active contours in image processing," Numerical Math, vol 66, 1993, pp. 1-13.

[37] Shashank M., Jayanthi S., R. Varma, L.T.Kishore, "A Novel framework for segmentation of stroke lesions in diffusion weighted MRI using multiple b-Value data", 21st Int. conference on Pattern recognition, IEEE, 2012, pp. 3762-3765.

[38] Myungeun Lee, Soonyoung Park, Wanhyun Cho, Soohyung Kim, and Changbu Jeong, "Segmentation of medical images using a geometric deformable model and its visualization," Can. J. Elect. Comput. Eng, vol 33, No. 1, 2008.

[39] Y.Kabir, M.Dojat, B.Scherrer, F.Forbes, C.Garbay, "Multimodal MRI segmentation of ischemic stroke lesions," 29th annual Int. conference of the IEEE EMBS, IEEE, 2007, pp.1595-1598.

[40] Tayel M., Abdou M, "A Neuro-difference fuzzy technique for automatic segmentation of region of interest in medical imaging. 23rd National Radio Science Conference," IEEE, 2006, pp. 1-7.