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CHRONOLOGY OF BRAIN TUMOR CLASSIFICATION OF INTELLIGENT SYSTEMS BASED ON MATHEMATICAL MODELING, SIMULATION AND IMAGE PROCESSING TECHNIQUES

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ABSTRACT

Tumor classification using image processing techniques is becoming a powerful tool nowadays. Based on the importance of this technique, the motivation of this review paper is to present the chronology of brain tumor classification using the digital images and govern the mathematical modeling and simulation of intelligent systems. The intelligent system involves artificial neural network (ANN), fuzzy logic (FL), support vector machine (SVM), and parallel support vector machine (PSVM). The chronology of brain tumor classification presents the latest part of the literature reviews related to the principal, type and interpretation of segmentation and classification of brain tumors via the large digital dataset from magnetic resonance imaging (MRI) images. This paper has been classified the modeling and simulation in classical and automatic models. Around 115 literature reviews in high ranking journal and high citation index are referred. This paper contains 6 contents, including mathematical modeling, numerical simulation, image processing, numerical results and performance, lastly is the conclusion to standardize the frame concept for the future of chronological framework involving the mathematical modeling and simulation. Research outcome to differentiate the tumor classification based on MRI images, modeling and simulation. Future work outlier in segmentation and classification are given in conclusion.

Keywords: *Tumor classification, Chronology, Intelligent systems, Mathematical modeling and simulation, Numerical results and performance*

1. INTRODUCTION

Brain is the most important organ overall the human body. Brain's strength lies in control of all parts of the body [1]. Besides , brain tumor is hazardous disease, wrong diagnosing of brain tumors causes severe results [2]. [1] Reported that in 2009, there were 12,920 death cases due to brain tumor in USA based on national cancer institute statistics. (MRI) Recently, MRI is the viable technique for studying the medical images. Good explanation for understanding MRI principals available in [3]. The main parameters to determine image intensity are proton density (PD), T1, T2, and T2* [1]. The main problem in MRI segmentation is labeling voxels according to their tissue types. This is involving white matter (WM), grey matter (GM), cerebrospinal fluid (CSF) and pathological tissues (tumor), etc. see, [4]. Thus, this research aimed to present the chronology of brain tumor classification using the digital images and govern the mathematical modeling and simulation of intelligent systems.

The notion of classification medical images is to find different features of categorization. Strategy of classification followed sequence of processes such that image processing technique, which involving detection, segmentation, feature extraction, feature selection, and then classification model construction. SVM is a state-of-the-art for classification grown up from statistical learning theory [5, 6] and [7, 8]. SVM has been widely used in several applications such as computer vision, data mining, computational intelligence.

Additionally, image classification, pattern recognition, automatic control, E-commerce, bioinformatics, remote sensing image classification, and information retrieval. Besides, big data set becomes a salient problem nowadays. In terms of GPU, there are several approaches and methodologies have been deliberated to accelerate the training process, see [9] and [10]. Other classifier techniques are FL and ANN. FL is set of mathematical principals based on degrees of classical binary logic. Fuzzy based methods are well known for automatic brain tumors segmentation and classification. These methods involved FCM [11], MFCM, and PFCM [12, 13]. ANN is inspired by the way biological nervous systems, like the brain. An ANN has observed ability to derive meaning of imprecise data [14].

This review concentrates on recent researches of detection, segmentation, and classification schemes for MRI brain tumor. The rest of this paper is organized as follows. Section 2 describes the Procedure of Identification and segmentation. Section 3 concentrates on mathematical models for popular intelligent systems. PSVM is the aim of Section 4 while Software and Hardware is the concern of Section 5. Results and discussion will be described in Section 6. Section 7 concludes the main points and provides some future work.

2. PROCEDURE OF IDENTIFICATION AND CLASSIFICATION

This section is aiming to describe the main steps of MRI brain tumor detection and classification. The first step is the detection process followed by basic stage, which called Preprocessing. Besides, to distinguish the type of tumor, two processes accomplish this task namely feature extraction and feature selection.

2.1 Detection

Several studies have been discussed to detect the brain tumor based on different resources. For instance, EEG, proton MR spectroscopy (MRS), long echo proton MRS signals. [15] successfully have enhanced accuracy of brain tumor detection by combining of MRI and MRS. Strategy of classification followed the major rules of image processing technique, which involving segmentation, feature extraction, feature selection, and classification model construction. Fuzzy possibilistic c-means (FPCM) has been used with parametric deformable method for tumor detection [16]. Based on Fuzzy technique, automated segmentation has been applied to spot brain mass boundaries. Obtained results show the effectiveness of this approach. This study showed that MRI with MRS yield better result than using MRI solitary 79.0% versus 69.0%. [17] Have applied improved kernel fuzzy C-mean (IKFCM) for rough detection.

2.2 Preprocessing

Preprocessing plays an important role in segmentation and classification like noise removing. Noise removing is the main issue in image classification. Thus, it is a key challenge for random and non-random processes to remove noise and immune to data. For example, Gaussian noise [18] and speckle noise [19] used in ANFIS. The ANFIS can be used for brain tumor segmentation, see e.g., [20-23]. [24] reported various de-noising methods. Linear, non-linear filters, Markov random field (MRF) models, linear diffusion methods, wavelet models, non-local means models, and analytically correction schemes. None of previous methods is better than others in terms of computational cost, thus it is still open problem for developing. Modifications of linear diffusion methods are available in [25-27]. Conditional Random Fields (CRF is an effective and regularization factor in terms of accuracy and removing noise [28]. [17] have applied improved kernel fuzzy C-mean (IKFCM) to solve noise sensitivity of FCM. To reduce the noise, [29] have used Kernel-Sobel-Low pass (KSL). Recently, Fast Discrete Curvelet Transform (FDCT) is an effective technique for removing noise from MR images [1].

2.3 Brain Tumor Characters, Feature Extraction, and Feature Selection

Researchers have proposed variety characters to classify the brain tumor in MRI involving symmetry, statistical, texture features, genetic expression, etc. However, feature extraction and feature selection play an important role in brain tumor classification. Feature extraction is the way of combining the variables, measuring data and dimensionality reduction. Firstly, [30] - based on dominant frequency features and multi-resolution metric- have described a method for face recognition. Second, [31], have used a number of reference images for extract features immediately. However, [32] have proposed feature extraction method based on Fisher discriminant analysis [33]. Based on enhanced stochastic learning, [34] have developed an effective method for feature extractions. [35] and [36] have portrayed a robust method of feature selection and extraction to characterize the tumor into five distinct features white matter, Gray matter, CSF, abnormal and normal area using Linear Discriminant Analysis

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(LDA). [37] have pointed out that wavelet transform is the best tool for image feature extraction. Feature selection is the process of selecting a subset of relevant features and speeding up learning process by removing redundant features [35].

2.4 Automatic Segmentation of Brain Tumor

Several methods have been discussed for MRI brain tumor segmentation. References such as [38-41] have divided segmentation techniques into four major classes: Threshold-based techniques, region-based techniques, pixel classification techniques, model-based techniques. Beneficial summary of segmentation methods like Threshold-based Global and Local Thresholding, Region-based Region-growing, Watershed, Pixel-based Fuzzy C Means, Artificial Neural Networks, Markov Random Fields, and Model-based Parametric Deformable Models have been discussed in terms of advantages and disadvantages [42]. [43] have discussed a comprehensive review of robust automatic segmentation methods in MR images. [43] divided automatic segmentation methods into main four techniques. Fuzzy based methods [11-13, 44] , Thresholding based Methods, Region Growing based Methods [45], and Clustering based Methods such as k-mean clustering, cluster index. K-means, fuzzy clustering (FCM), and local correntropy-based k-mean cluster [46-48].

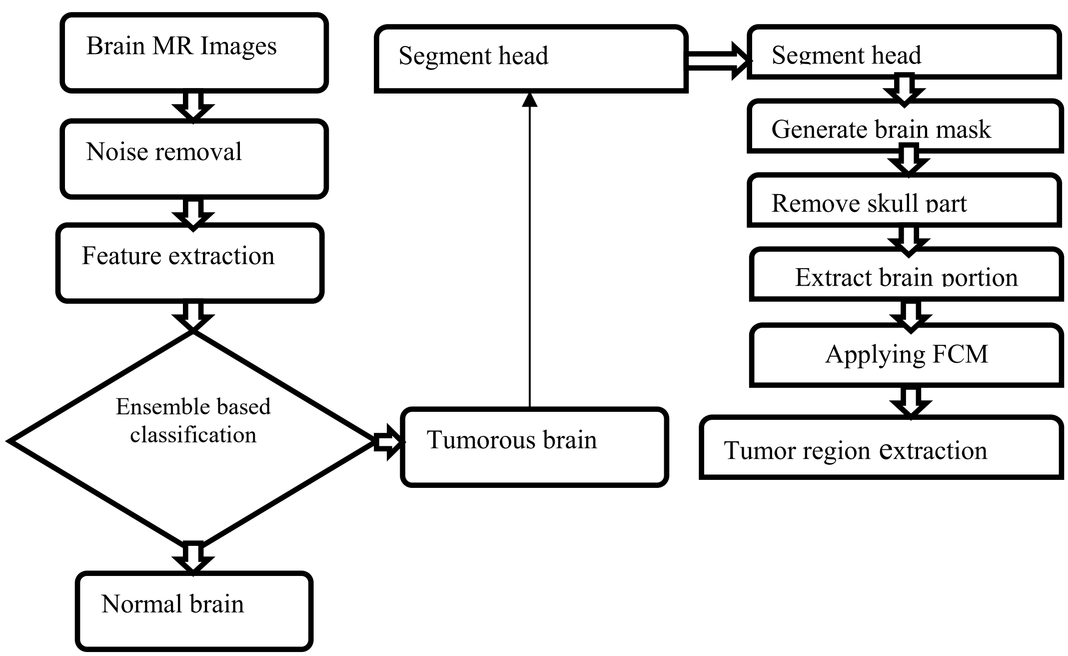

Figure1: Proposed system in [1]

Automatic systems for brain tumor segmentation still interesting area for future evolutions. Manual segmentation of brain tumor requires time and experience, which indicates to looking for easier and automatic methods. Recently, in medical image processing, automatic segmentation plays an important role in analyzing diverse pathological tissues [37]. Classical, fuzzy, neural networks and others are well-known techniques for automatic brain tumors segmentation and classification. Classical techniques uses thresholding, edge and region based methods. Fuzzy segmentation technique is useful for multichannel images but not for single channel images, while neural network techniques are applied only for some types of images [4].

Useful automatic models for brain tumor segmentation have been described in [42] survey. For example, Discriminative Random Fields and Support Vector Machines, Fuzzy Region Growing Framework [49], Model-based Fuzzy classification [16], Self-Organizing Maps [45], and the recent powerful proposed techniques form 2010 up to 2012 are Knowledge-based Fuzzy classification, Knowledge-based/Neural Networks, Region-based active contour models, and Genetic Algorithm Clustering/Region Growing, see respectively [50-53]. Further up, [17] have introduced an automatic segmentation and classification of brain tumors using deformable models and fuzzy classification. Improved kernel fuzzy C-mean (IKFCM) has been applied for rough detection and solve noise sensitivity of FCM. Behind extraction process, MR images have been classified into five categories: Tumor, cerebrospinal fluid, white matter, gray matter and background. Mathematical equations and formulas of IKFCM and deformable models are available in [17]. Besides, [28] have presented another approach of automatic segmentation and classification for MR images. This method based on SVM using multispectral intensities with hierarchical regularization, which based on conditional random fields (CRF). Hierarchical way includes white matter, gray matter and necrotic, active, edema region respectively. By means of accuracy and removing noise, CRF regularization factor was an effective tool.

A robust automatic system to classify the brain tumors has been proposed by [1]. Obtained results yield high accuracy passed 99%. The medical images of MRI have been classified by SVM. Fuzzy C-Means Clustering (FCM) technique used to clustering the tumor region from normal brain. Fast discrete Curvelet transform (FDCT) is an effective technique for removing noise from MR images. This system one of the recommended systems in brain tumors classification.

According to [54] have explained a gentle review on automatic brain tumor classifying system from MRI based on Gabor Wavelet. Three main steps have been described: Removing the noise and preprocessing by wavelet transform, edge detection process by Gabor filter, and finally segmentation by threshold method.

3. SYSTEMS AND MATHEMATICAL MODELING OF INTELLIGENT SYSTEMS

3.1Detection of Brain Tumor

Several studies have been discussed the mathematical schemes to detect the brain tumor. This sector explains some of well-known models.

3.2 Parametric deformable method

Parametric deformable method (PDM) is a successful model to refinement, detection, and segment internal brain structures [55-57]. The segmentation obtained from the previous processing is transformed into a triangulation using an isosurface algorithm based on tetrahedral and is decimated and converted into a simplex mesh Z, see [16] and[17] . The progress of the deformable surface Z is defined by the following dynamic force equation:

$$\gamma \frac{\partial Z}{\partial t} = F_{int}(Z) + F_{ext}(Z), \tag{6.1}$$

where F_{int} is the internal force that specifies the regularity of the surface and F_{ext} is the external force that drives the surface towards image edges. The selected internal force obtained by

$$F_{int} = \alpha\nabla^2 Z - \beta\nabla^2(\nabla^2 Z), \tag{6.2}$$

where ∇^2 is the Laplacian operator, α and β control the surface tension and rigidity respectively. Then finite difference method utilized to discretize the equation on the simplex mesh [58]. Therefore, the external force is derived from image edges as follow.

$$F_{ext}(Z) = v(x, y, z), \tag{6.3}$$

Where v is a Generalized Gradient Vector Flow (GGVF) field introduced by [58-61], v is computed by diffusion of gradient vector of a given edge map and defined as the equilibrium solution of the following diffusion equation:

$$\frac{\partial v}{\partial t} = g(\|\nabla f\|)\nabla^2 v - h(\|\nabla f\|)(v - \nabla f), \tag{6.4}$$

$$v(x, y, z, 0) = \nabla f(x, y, z), \tag{6.5}$$

where f is an edge map and the functions g and h are weighting functions which can be chosen as follows:

$$\begin{cases} g(s) = & e^{-\frac{s^2}{k}} \\ h(s) & = 1 - g(s) \end{cases} \tag{6.6}$$

To compute the edge map, a linear spatial filtering which is usually associated to Canny-Deriche edge detector is applied.

3.3 Improved kernel fuzzy C-mean (IKFCM)

Novelty of IKFCM is obtained by [62]. Recently, IKFCM has been applied for rough detection and solve noise sensitivity of FCM [17]. Mathematical model of IKFCM given by

$$J_{fcm}(U, V) = \sum_{i=1}\sum_{j=1} u_{ij}^{m} \; \|X_k - V_i\| \tag{6.7}$$

subject to $\sum_{i=1}^{c}\sum_{j=1}^{n} u_{i,j} = n,$ (6.8)

and conditions $\sum_{j=1}^{n} u_{i,j} > 0,$ (6.9)

$$u_{i,j} \geq 0,\ 1 \leq i \leq c,\ \ 1 \leq j \leq n, \tag{6.10}$$

where X_k presents the characteristics of a point to be classified (e.g., gray level), V_i is the class

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center, while c is number of classes and n is number of points to be classified, u_{ij} is the membership of points X_k to class i. The optimization formula of function J given by

$$u_{ij} = \frac{n(1-K_g(x_j,v_i))^{\frac{1}{1-m}}}{\sum_{p=1}^{c}\sum_{k=1}^{n}(1-K_g(x_k,v_p))^{\frac{1}{1-m}}}, \quad (6.11)$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} K_g(x_j,v_i)}{\sum_{j=1}^{n} u_{ij}^{m}},$$

(6.12)

3.4 Feature extraction and selection models

Feature extraction and feature selection play an pivotal role in brain tumor classification. This section describes some popular mathematical models for extracting and selecting brain tumor features.

3.5 Linear Discriminant Analysis (LDA)

LDA is a statistic method used for linear combination of features. LDA creates a linear combination to yield the largest mean differences between given classes. According to [36], the mathematical model given in terms of two measures. First, within-class scatter matrix obtained by

$$Sw = \sum_{j=1}^{c}\sum_{i=1}^{N_j}(x_i^j - \mu_j)(x_i^j - \mu_j)^T,$$

where μ_j is the mean of class j, x_i^j is the ith sample of class j, c is the number of classes, and N_j is the number of samples in class j. Second, between-class scatter matrix given by $Sb = \sum_{j=1}^{c}(\mu_j - \mu)(\mu_j - \mu)^T$, where μ is the mean of all classes.

3.6 Wavelet Transform (WT)

Wavelets are mathematical functions used to export image features. Hence, this functions decompose data into different frequency components and study each component with a resolution matched to its scale [63]. In other words, wavelets are functions generated from basis function called the mother wavelet by dilations and translations in time (frequency) domain [64]. Suppose φ is the mother function, then other functions can be represented by

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi\left(\frac{t-b}{a}\right),$$

(6.14)

where $a, b \in \mathbb{R}$, arbitrary and represent the parameters for dilations and translations respectively in the time axis. However, Discrete Wavelet Transform (DWT) is the implementation of the WT using a discrete set of the wavelet scales and translation under some basic rules [65]. The discretized scale and translation parameters are given by $a = 2^{-j}$ and $b = k2^{-j}, j, k \in \mathbb{Z}$. Hence, wavelet functions' family is obtained by

$$\varphi_{j,k}(t) = 2^{\frac{j}{2}}\varphi(2^{j}t - k).$$

(6.15)

Another type of DWT is called Undecimated Wavelet Transform (UDWT), see [66].

3.6.1 Gabor Wavelet (GW)

GW is a popular filter in area of texture analysis and image segmentation [67-69]. This filter is used to extract the texture features of tumor image and analysis of regions of interest (ROIs) [54]. Mathematically, the filter can be defined as

$$\psi(x',y',f,\theta) = \frac{f^2}{\pi\eta\gamma}e^{-\left(\frac{f^2}{\gamma^2}x'^2+\frac{f^2}{\eta^2}y'^2\right)}e^{j2\pi f x'}$$

(6.16)

$$x' = xCos(\theta) + ySin(\theta), \quad y' = -xSin(\theta) + yCos(\theta)$$

(6.13)

where θ is the rotation angle of both the Gaussian major axis and the plane wave, f is the central frequency of the sinusoidal plane wave. η is the sharpness along the minor axis conversely γ for major axis. The sharpness values for both major and minor axis are set to 1. Suppose $M(x,y)$ is an image, then Image texture features using Gabor filter obtained by

$$g(x',y',f,\theta) = M * \psi(x',y',f,\theta).$$

(6.17)

3.7 Segmentation models

Recently [42] have divided segmentation techniques into four major classes: Threshold-based techniques, region-based techniques, pixel classification techniques, model-based techniques.

3.8 Threshold-based methods (TBMs)

Thresholding is a simple region segmentation method based on compare intensities of an image with one or more intensity thresholds. TBMs classified into two sub-methods, namely global and local thresholding. Local segmentation utilized for more than two regions, while global for segment two regions solely. The mathematical expression of global thresholding is obtained by

If g(x, y) is a thresholded version of f (x, y) at some global threshold T, then

$$g(x,y)=\begin{cases}1 & \text{if } f(x,y)\geq\rho,\\ 0 & \text{Otherwise,}\end{cases}$$

(6.18)

such that pixels with value of 1 refer to the ROI, while value 0 correspond to the background.

3.8.1 Region-based methods

Based on predefined similarity criterion [38], this method forms separate regions by merging neighborhood pixels with homogeneity properties. Let Y be an image that is segmented into m regions, each of which is denoted as R_i, where i = 1, 2,, m. The original image can be exactly assembled by putting all regions together and there should be no overlapping among any two regions R_i and R_j for i ≠ j. The logical predicate L (□) contains a set of rules (usually a set of homogeneity criteria) that must be satisfied by all pixels within a given region, and it fails in the union of two regions since merging two distinct regions will result in an inhomogeneous region. The regions must satisfy the following properties:

$$Y=\bigcup_{i=1}^{m}R_i,\quad R_i\cap R_j=0\quad \forall i,j=\overline{1,m}$$

$$L(R_i)=True \text{ for } \quad i=\overline{1,m}$$

$$L(R_i\cup R_j)=Falas \text{ for each } i,j=\overline{1,m}: i\neq j.$$

(6.19)

Region growing and Watershed are the most popular techniques of region-based methods. Region growing is the simplest region-based segmentation technique, which used for extraction process of similar pixels from an image [70]. [71] implemented this method to segment MRI brain tumors. [72-74] have proved that region-based methods are better than non-region in terms of effective and computation effort. Further studies in this field available in [75-79]. However, using multi-scale watershed transformation, [80] and [81] implemented Watershed method to segment MR images brain tumor. [82] have proposed this technique based algorithm that was used for detection of tumor in 2D and 3D brain MR.

3.8.2 Pixel Classification Methods

In brain tumor segmentation the methods based on pixel classification are constrained to the use of supervised or unsupervised classifiers to cluster pixels in the feature space. Measure that is commonly used as similarity criterion is the normalized inner product, which is given by:

$$nd(x_i,x_j)=\frac{x_i^T x_j}{||x_i||\,||x_j||} \qquad (6.20)$$

where T denotes the vector transpose operation. This measure provides information regarding the cosine between the vectors x_i and x_j in the feature space. On the other hand, three approaches fall under this category, which are Fuzzy C-Means, Markov Random Fields, and Artificial Neural Networks. FCM clustering is a very popular technique in the area of unsupervised image segmentation by pixel classification, particularly in the case of brain tumor segmentation [83] and [84]. The fuzzy membership functions, constrained to be between 0 and 1, reflect the similarity degrees between the data value at a specific location and the prototypical data value, or centroid, of its class. Further details for Fuzzy C-Means attitude and enhancements given in references [85-94]. Fuzzy C-Means algorithm obtained by [95] and [84]. Let $Y=\{y_1,y_2,\ldots,y_N\},\forall y_i\in R^p$ be a set of N vectors clustred into C groups of similar data and p is real-valued measurements to represent features of the object y_i. If $v_{i,j}\in[0,1]$ expresses the C-partition matrix, then $v_{i,j}$ satisfies the following properties

$$\sum_{i=1}^{C}v_{i,j}=1 \text{ and } j=1,2,\ldots,N,$$
$$0<\sum_{j=1}^{N}v_{i,j}<N \text{ and } i=1,2,\ldots,C.$$

(6.21)

y_i are represented by the cluster center vector $u_i\in U=\{u_1,u_2,\ldots,u_C\}$ and $u_i\in R^p, 1\leq i\leq C$. The aim of Fuzzy C-means algorithm is to minimize an objective function

$$J_m(V,U)=\sum_{i=1}^{C}\sum_{j=1}^{N}(v_{i,j})^m\,||y_j-u_i||^2, m\geq 1.$$

(6.22)

$m=2$ is widely used as a good Fuzzy parameter [96]. Fuzzy C-means updating process given by

$$u_i=\frac{\sum_{j=1}^{N}(v_{i,j})^m y_j}{\sum_{j=1}^{N}(v_{i,j})^m}, i=1,2,\ldots,C$$

(6.23)

$$v_{i,j}=\frac{1}{\sum_{k=1}^{C}\left(\frac{||y_j-u_i||}{||y_j-u_k||}\right)^{\frac{2}{m-1}}}, \quad j=1,2,..,N.$$

(6.24)

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However, unsupervised clustering method of Markov Random Fields (MRF) provides a way to integrate spatial information into the clustering process [97] . MRF and Conditional Random Fields (CRFs) techniques are able to represent complex dependencies among data instances, giving a high accuracy on brain tumor's segmentation task [98]. In contrast, supervised clustering method is the Artificial Neural Network (ANN). ANN approaches are non-parametric techniques. Clarke [99] was one of the first researchers to introduce a supervised classification using an ANN technique for brain tumor segmentation in MR images. Artificial Neural Network (ANN) is inspired by the way biological nervous systems, like the brain. An ANN has observed ability to derive meaning of imprecise data [14]. Besides, based on learning vector quantization (LVQ), [14] have proposed modified Probabilistic Neural Network (PNN) to achieve successfully the brain tumor classification in MRI with remarkable accuracy 100%. However, Self-organizing map (SOM) is widely used and distinguished amongst neural network (NN) algorithms [100]. SOM is a software tool for the visualization of high-dimensional data, see e.g., [101-103].

3.8.3 Model-Based Segmentation Techniques (MBST)

MBST is an effective way to overcome 3D image segmentation. MBST can be divided into two categories namely Parametric Deformable Models (PDM) and Geometric Deformable Models or Level Sets.

I. Parametric Deformable Models (PDM)

Contour deformable models have been widely used for its sensitivity in looking for the boundary of brain tumors. In fact, the sensitivity of the boundary found by the snake is better than the conventional edge detection methods, such as the Sobel and Laplacian. PDM is known as snakes or active contour models defined as an ordered collection of n points in the image plane $U = \{u_1, u_2, \dots, u_m\}, u_i = (x_i, y_i), i = \{1, 2, \dots, m\}$. The points in the contour iteratively approach the boundary of an object through the solution of an energy minimization problem. For each point in the neighborhood of u_i, an energy term is computed:

$$E_{snake}(U) = E_{int}(U) + \beta E_{ext}(U),$$

(6.25)

where E_{int} is an energy function dependent on the shape of the contour and exit (U) is an energy function dependent on the image properties, such as the gradient, near point u_i. β are constants providing the relative weighting of the energy terms [42]. However, Active control model primary proposed by [104], which based on $X(t) = [x(t), y(t)]$ deforms to minimize an energy function E as follow.

$$E = \frac{1}{2}\int (\alpha |X'(t)|^2 + \beta |X''(t)|^2) + E_{ext}(X(t))dt$$

(6.26)

II. Level Sets

Level Sets are methods to overcome difficulty of PDM to handle topological changes for the splitting and merging of contours naturally[105]. The main component of the level set method is the interface. If the interface is represented by Γ, Γ is expresses the zero level set $\{\varphi = 0\}$ of a level set function φ. The function is a surface defined over the image area with the following property:

$$\varphi(x, y, t = 0) = \pm d(x, y),$$

(6.27)

where d is the distance function from a point (x, y) to interface Γ(t = 0), and the plus (minus) sign is select if the point is outside (inside) the initial interface. Hence, the surface φ changes along its normal direction with speed H as:

$$\frac{\partial \varphi}{\partial t} + H|\nabla \varphi| = 0 \text{ with } \varphi(x, y, t = 0)$$

(6.28)

The propagating front at any time is given by the zero level set $\Gamma(t) = \{(x, y) | \varphi(x, y, t = 0)\}$.

3.9 SVM

The goal of SVM is separating the data with hyperplane and extends this to non-linear boundaries using kernel trick. In linear separable date, SVM tries to minimize the training error with the formula that maximizes distance from their closest points [36].

$$\omega . x + b = 0, \quad (6.29)$$

while ω and b are weight and bias parameters respectively. Regard to separate classes, we define the maximal margin hyperplane as follow.

Minimize $\frac{||\omega||^2}{2}$ and $y_i(\omega . x + b) \geq 1; y_i \in \{-1, 1\}, i = 1, 2, \dots, n$.

(6.30)

This is called non-linear optimization problem with inequality constraints, which can be solved by Lagrange multipliers.

Maximize

$$\sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} y_i y_j a_i a_j x_i^T x_j, \quad (6.31)$$

subject to

$$\sum_{i=1}^{l} a_i y_i = 0, a_i \geq 0, \quad (6.32)$$

the solution obtained by

$$\omega = \sum_{i=1}^{l} a_i y_i x_i. \quad (6.33)$$

4. PSVM

4.1 Overview

SVM has been widely used in data-mining and Big Data applications as modern commercial databases start to attach an increasing importance to the analytic capabilities [106]. The core notion of SVM is a quadratic programming problem (QP), which is separating support vectors from the training data. Several applications recently however are more complicated and have a big data. Therefore, developed technology shifted towards parallel platforms. There are a dramatically develops in Parallel computing. According to [9], classification by training SVM remains suffer of intensive computations. However, in terms of big data, SVM suffers of time consuming and memory limitation. Therefore, to overcome this problem, parallel SVM (PSVM) is the recent solution to reduce memory use and accelerate the process. According to [107], PSVM became a source available for download at http://code.google.com/p/psvm/. The key of PSVM is parallel Cholesky Factorization (ICF). Let m be the number of training samples, d be the redused matrix dimension and n be the number of machines. PSVM reduces the memory requirement from $O(n^2)$ to $O(np/m)$

The key challenge in machine learning algorithms is time consuming. Recently, Graphics Processor unit (GPU) becomes a widely significant tool to speed up algorithms. Using Platt's Sequential Minimal Optimization algorithm, [9] have described a high-performance solver for SVM trainning, which achieved speedups of 5-32× over LibSVM running on traditional Processor. Moreover, [9] built a system for SVM classification hits the peak of 120-150× over LibSVM. A gentle explanation of various parallel optimization techniques for SVM on multicore CPUs and GPUs has been described by [108]. This study covered both explicit and implicit parallelization methodologies. [108] pointed out those most existing parallel implementations either on multi core or GPUs are explicit parallelization based on SMO algorithm. Nevertheless, comparison with implicit parallelization, [108] found that implicitly parallel algorithm is simple, efficient, permits a much implementations in SVM training.

4.2 Methodology of Parallelization on SVM

Big data set becomes a salient problem nowadays. In terms of GPU, there are several approaches and methodologies have been deliberated to accelerate the training process. [9] have presented SVM solver on GPU successfully based on Sequential Minimal Optimization (SMO) algorithm. However, the result is not satisfied compared to LIBSVM according to [10].

Carpenter used the same SMO algorithm, but in different methodology, which based on hybrid of double and single precision arithmetic unlike [9] who used solely single precision. The result is better than [9] results, but still not duplicate the LIBSVM results. Finally, [109] have presented LibSVM on GPU preserved all original features of the library as well as overcome the last methods' drawbacks and achieved a maximum performance as well. The followed methodology of classification by [109] namely based on two separate tasks. Computing of the kernel matrix (KM), and SMO solver to build the model. The acceleration process has been presented into two main parts. Avoiding the recalculation of the KM by passed it to SVM during the validation loops. Second, the parallelization on GPU to speed up the process.

5. SOFTWARE AND HARDWARE PARALLEL

Varity parallelization techniques have been discussed to solve data deluge. Each technique has its own usability characteristics such that threads, MPI, MapReduce, and mash-up. Recently, MPI is a classical model in many SVM methods. However, it is not useful in scale data and data mining problems. Therefore, another model is applicable for those massive data called MapReduce. MapReduce is a robust distribution-computing model to procedure huge data set. One of this model advantages is providing the software. [110] have studied the parallelism of SVM based on iterative MapReduce model using Twister software. MapReduce is cloud technology, one of the most famous MapReduce architectures is Google, but the source is not open. Hadoop is the popular and open source software MapReduce. Most well-known companies such as Yahoo, Facebook, eBay used Hadoop software. Despite this, Hadoop does not support iterative Map. Sequentially, Prof Fox

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developed software called Twister to support iterative and non-iterative MapReduce applications, which applicable on cloud platform.

Besides of that, n-fold cross validation is commonly used to identify the best hyperparameters for SVM. This becomes a weak point of SVM due to the extremely long training time for various hyper parameters of different kernel functions. [111] have proposed a method to accelerate the cross validation procedure by running multiple training tasks simultaneously on GPU. Comparison tests have shown that the proposed method is 10 to 100 times faster compared to the state-of-the art LIBSVM tool. [112] have proposed a soft computing model for segment brain tumor in MRI using HSOM.

6. RESULTS AND PERFORMANCE

This review paper described the modern techniques and mathematical models to segment and classifies the brain tumor. Several systems showed the procedure of classification. Comprehensive idea behind robust classification is the process of perfect detection and noise removing. First step of classification is to detect the brain tumor spot. For example, EEG, proton MR spectroscopy (MRS), long echo proton MRS signals, FPCM, IKFCM and Parametric deformable method. Second, preprocessing technique such as noise removing procedure. For instance, Gaussian noise, speckle noise, Markov random field (MRF), wavelet models, CRF, IKFCM, and recently FDCT. Third, feature extraction and feature selection such as LDA, WT, DWT, and GW. According to [37], wavelet transform is the best tool for image feature extraction. Forth is segmentation process, there are diverse segmentation methods involved manual segmentation, semi-automatic segmentation, and automatic segmentation. This paper focused more on automatic segmentation due to modern technology and recent parallelization programs to solve complicated and big data set. Besides well-known classifiers SVM is preferred model to classify the brain tumor compared to ANN classifiers. In contrast, PSVM is a modern scheme to parallelize SVM to yield accurate results with massive data as well as faster in terms of time consuming. Thus, in this research we review the chronology of brain tumor detection and classification via using modern technology, such as the digital images and govern the mathematical modeling and simulation of intelligent systems.

On the other hand, In terms of automatic segmentation, we recommend to use [1] system. This system yield high accuracy passed 99% based on SVM, FCM, and FDCT. By means of neural network, we suggest to apply modified Probabilistic Neural Network (PNN), which yielded remarkable accuracy 100% obtained by [14]. Besides, in terms of Fuzzy, PSO is superior model compare to HSOMFCM, and GA approaches. Modern technology provides some intelligent software for brain tumor detection and classification. For instance, Brain Visa, FSL, and BrainSuite are software for brain segmentation. Twister is the software of parallelize SVM. Alternative software for parallel process is Hadoop, which is open source. LIBSVM is well-known library and software for SVM.

7. CONCLUSION

Based on the importance of image processing technique, the motivation of this review paper is to present the chronology of brain tumor detection and classification using the digital images and govern the mathematical modeling and simulation of intelligent systems. The intelligent system involves artificial neural network (ANN), fuzzy logic (FL), support vector machine (SVM), and parallel support vector machine (PSVM). The chronology of tumor classification presents the latest part of the literature reviews related to the principal, type and interpretation of segmentation and classification of brain tumors via the large digital dataset from magnetic resonance imaging (MRI) images. Furthermore, this study focused on automatic models and parallelizing of SVM using GPU for dealing with complex and big data set. Brain tumor is hazardous disease, wrong diagnosing of brain tumors causes severe results. This study reviewed recent references for diverse techniques for detection, segmentation and classification MRI brain tumor. Modern intelligent techniques to detect and classify MR images brain tumor have been discussed. Consequently, we appraise various well-known approaches like SVM, PSVM, FL, and ANN.

To finalize this study, we provide some future works for interested researchers. First, segmentation methods based on preprocessing techniques like de-noising methods, which none of them better than others in terms of computation cost, thus it is still open problem for developing. Second, computer-aided detection (CAD) still open problem since CAD system does not work in all cases regarding database size and quality. Third, notion of integrate techniques in one hybrid system still open gaps for future work.

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