Intelligent Detection Of High Grade Brain Tumor With Moment Invariant Features And Adaptive Clustering

A. Murugan, M. Dhamodaran, S. Jegadeesan.

Abstract— Earlier diagnosis of Astrocytoma brain tumor significantly increases the survival rate of the human brain tumor along with the treatment. In higher-grade Astrocytoma brain tumor, Glioblastoma is an aggressive and incurable malignant primary tumor. Hence a new intelligent diagnostic system is proposed in this article to detect the high-grade brain tumor, which is comprised of moment invariant feature extraction and automatic clustering. In this approach, the moment invariant features are used to describe the certain shape parameter relevant to the tumor region and dead cells are measured by the seven central moments. As long as the shape of the higher grade tumor is recognized with the feature detection, the white matter, gray matter, and cerebrospinal fluid are clustered from which, the cancerous cells in the cerebrospinal fluid and dead cells with the white matter are diagnosed. The contextual information is manipulated in accordance with the noise information such that the noises and outliers over the local window of MR image are removed efficiently. As a result, an accuracy of 98.2 with Anaplastic Astrocytoma tumor and 98.4 with a Glioblastoma brain tumor is obtained which outperforms the traditional system efficiently.

Index Terms— Cancer death, contextual clustering, Glioblastoma Multiforme, high grade brain tumor, moment invariant features,

1 INTRODUCTION

In 2020, the projected cancer death in the united states is about 606,520 among the new cancer case of 1,806,591, and the Glioblastoma brain tumor death rate has been significantly increased due to higher grade malignancy of brain tumor [2]. Therefore the diagnosis of brain tumor in earlier stage increases the survival rate of the patients along with the treatment. In brain tumor anatomy, the uncontrolled cell growth within the brain structure formulates the brain tumors, which make an impact in all ages of people. Tumors can be developed in any part of the brain region with any shape and size. The tumors in the central spinal canal or inside the cranium are described as a brain tumor. It also presents as an edema and necrosis. In fact, the head injuries, continuous radiation therapy, electromagnetic fields, formaldehyde and vinyl chloride are the general cause of the brain tumor. The primary brain tumors are originated within the brain region and do not invade to another part of the organ where as the secondary tumors are metastatic and developed from another part of the cancerous organ like breast cancer or lung cancer. It may be benign (non-cancerous) or malignant (cancerous) tumor.

The benign tumor having well described edges with slow abnormal cell growth and can be cured with proper prior treatment. The malignant tumor is referred as cancerous cells experience the rapid growth and easily spread to the neighboring healthy cell. In general, the glial cells formulate the gliomas tumor. The astrocytes from glial cells formulate the Astrocytoma tumor with different Astrocytoma tumor, in which Pilocytic Astrocytoma belongs to grade I tumor, grade II astrocytoma, Anaplastic Astrocytoma as grade III tumor and Glioblastoma multiforme is a grade IV tumor. Glioblastoma is highly malignant, aggressive and most threatening brain tumor. Typically, the accumulation of a tumor cell is continuing even it is surgically eradicated [3,4]. Georgiadis et al. [5] addressed that the MRI is the non-invasive modality which assist the Radiologist and Neurosurgeon in diagnosing the abnormal brain tumor and effectively investigate the tumor anatomy, cellular structure, and vascular supply details. Since the anatomy or pathology of an image does not illustrate sufficiently with the T1 and T2 weighted image, the gadolinium substance is injected to illustrate the tumor region [3]. The T1, T2 weighted images and T1 contrast enhanced Glioblastoma brain tumor image are depicted in Fig. 1.

Fig. 1. MR images (a) T1 weighted image (2) T2 weighted image (c) Enhanced T1 weighted Glioblastoma brain tumor image

In brain tumor segmentation, Gordillo et al. [6] demonstrate the survey of tumor image segmentation techniques in which the abnormal brain tissue (active tumor, edema) with WM, GM, and cerebrospinal fluid (CSF) are separated along with edema from the normal brain image. The precise detection and analysis of abnormal tissue is difficult task compared to the normal brain tissue detection. A multiclass brain tumor segmentation and feature extraction with PCA is also implemented in [7] and the tumor image is classified with ANN in which Astrocytoma primary tumors, and Metastatic secondary tumors are investigated and the Artificial Neural

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Dr. A. Murugan is working as Professor in the dept. of Electronics and communication Engineering in M.Kumarasamy college of Engineering. The area of interest is Medical image processing and pattern recognition. Email: rasimurugan2k2@gmail.com

Dr. M. Dhamodaran is working as Professor in the dept. of Electronics and communication Engineering in M.Kumarasamy college of Engineering. The area of interest is image processing and measurements. Email: dhamodaranm.ece@mkce.ac.in

Dr. S. Jegadeesan is working as Associate Professor in the dept. of Electronics and communication Engineering in M.Kumarasamy college of Engineering. The area of interest is imaging technique and sensor Networks. Email: jegadeens.ece@rediff.com
Network is incorporated for the classification. This approach achieves 77 to 91% accuracy in classification with the accuracy of GBM—88.46%, AS—90.74%, MET—85%. The contrast details of human brain tumor image are incorporated with Type-II fuzzy approach, especially in Astrocytoma tumors with T1-weighted Magnetic Resonance Images [8]. Here the fuzzy rule based filtering is used in preprocessing and the possibilistic FCM clustering with fuzzy type II system are used to develop the type II Approximate reasoning approach along with threshold based feature extraction. It performs well in diagnosing the brain tumor grade with higher accuracy.

The malignancy of diffuse gliomas is evaluated in computer-aided diagnosis (CAD) system by using quantitative magnetic resonance imaging (MRI) features which facilitate the accuracy of 76%, 83%, and 88%, respectively. In this approach, the lower-grade gliomas are well distinguished from the Glioblastoma brain tumor [9]. Segmentation of MRI brain image with Fuzzy c mean is preferable soft clustering approach proposed in which the image details are preserved significantly than the hard clustering [10]. However, the FCM algorithm fails in segmenting the images corrupted by noise, outliers and artifacts. In conventional FCM clustering, the noisy pixels and artifacts are classified in a defective way due to its abnormal feature data. So the objective functions of this FCM clustering is modified in the variant of the FCM algorithm with the labeling of immediate neighbor pixel and constitutes the piecewise-homogeneous labeling [11]. This modified approach limits the image with single feature input. Chen & Zhang [12] introduce the variant of FCM, in which the median filtered image in FCM_S2 and mean filtered image with FCM_S1 are replaced in advance such that the neighborhood term in FCM_S, is modified. However, this approach is not robust to noise and outliers in an image, the objective function of FCM (KFCM) uses the new kernel distance measure along with the penalty term which influences the neighborhood on the central pixel. But the penalty term involved in each iteration decelerates the segmentation processes [13].

In order to optimize the computation, Chen & Zhang [14] adaptively incorporates the Gaussian function as kernel in mean filtered and median filtered KFCM_S variant to improve the image segmentation. The contextual information with the local window and the weighted parameter with the new kernel is used to achieve the robust to noise and outliers characteristics in the KFCM_S1 and KFCM_S2 segmentation [15].

The observations notified in the traditional techniques are

1. In adults, higher grade tumors are the most incurable malignant primary tumors.
2. The average tumor segmentation accuracy with the traditional methods is not optimum.
3. The segmentation becomes a challenging task due to Noise variation in each elements of MR image.

The organization of the articles is as follows. Section I addresses the different types of tumor and traditional detection approach. The proposed method are described in section II. Section III illustrates the results and discussion, finally the conclusions are addressed in section IV.

2. PROPOSED METHODOLOGY

In order to solve the observation experienced with the traditional system, we propose the new CAD system which comprises of moment invariant feature extraction and adaptive clustering. In this approach, the shape feature with moment invariant feature is determined. As long as the shape of higher grade tumor is recognized with the feature detection, the adaptive contextual clustering is initiated to cluster the brain image as GM cluster; WM cluster, and cerebrospinal fluid (CSF) cluster from which the cancerous cells and dead cells are detected.

![Fig. 2. proposed system in detection of high grade tumor](image)

2.1. Moment Invariant Features

In feature extraction, the shape of the brain tumor is investigated with the Moment invariant features [16] which are used to diagnose the mass area or the cystic information of cancerous cells in the CS fluid and the dead cells with the white matter of the Glioblastoma tumor are identified. The adaptive clustering is used to segment the CSF cluster and white matter cluster of the brain image such that the abnormal region of the brain image is recognized. Here the set of invariant features describes the algebraic invariants which are incorporated to investigate the shape moment of the tumor tissue in malignant tumor and Glioblastoma tumor as well as dead cells in Glioblastoma tumor. The two-dimensional moments are formulated from the $M \times M$ size digital image with the gray function $f(x, y), (x, y = 0, \ldots, M - 1)$ which is defined as

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} (x - p)^p (y - q)^q f(x, y); p, q = 1, 2, 3, n \quad (1)$$

The moment is formulated with the gray function $f(x, y)$ is manipulated with (a,b) can be defined as

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} (x + a)^p (y + b)^q f(x, y) \quad (2)$$

Here the central moment can be measured with the determined moments which is described as

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} (x - \bar{x})^p (y - \bar{y})^q f(x, y) \quad (3)$$

In this formula, $\bar{x} = \frac{m_{00}}{m_{10}}$, $\bar{y} = \frac{m_{01}}{m_{00}}$,

The normalized central moment can be defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}}; \quad \gamma = \left[ (p + q) / 2 \right] + 1 \quad (4)$$

An invariant characteristic over tumor scale, position and orientation are measured by the seven moments which are derived from third order normalized central moment.
2.2. Clustering

In brain tumor image, the cancerous cells are typically accommodated with the CSF cluster and the Necrosis in grade 4 tumor (GBM) are accommodated with the white matter. In addition, the brightest part in T1 weighted image illustrates the cancerous cells or tumor region and dark portion reflects the dead cells. In order to analyze the higher grade tumor, the brain tumor image is segmented as white matter (WM) cluster, gray matter (GM) cluster and the cerebrospinal fluid (CSF) clusters, therefore the automatic clustering for MR brain image is incorporated in our proposed CAD system. Since the quantity of noises in every element of an MR image is unpredictable and the pixel being processed is adaptive to the noise level, as a result, the MR imaging modality has become a challenging task. Similarly, in formulating regularization term is tedious. Hence the new parameter is substituted adaptively for the pixel being clustered to formulate the contextual details of an image such that the cluster is robust to noise and outliers. However, the total amount of noise over the image influences the pixel quality of an image. In order to detect the variation in gray information and normalize the local average grayscale of an image, initially, the Variation Coefficient (VC) is measured. Normally VC is large when the correlation among the center pixel of a local window and its neighbors is high with a high noise level. The VC implies the manipulation of each pixel coefficient of an image is described as

\[ VC_i = \frac{\sum_{k \in N_i} (x_i - \bar{x})^2}{N_k \cdot \bar{x}^2} \]  

(5)

Here \( x_i \) is the pixel belong to gray level with the window \( N_i \), \( N_k \) is the cardinality of \( N_i \). \( \bar{x} \) describes the mean of \( x_i \). The weight factor is defined as

\[ w_i = \frac{\exp\left(\sum_{k \in N_i} VC_i\right)}{\sum_{k \in N_i} \exp\left(\sum_{k \in N_i} VC_i\right)} \] 

(6)

In general, the average gray pixel is substituted over every pixel in an image with the weighting factor \( w_i \) which influences the formulation of contextual information which is described as

\[ \varphi_{ij} = \begin{cases} 
2 + w_i; x_i < x_j \\
2 - w_i; x_i > x_j \\
0; x_i = x_j 
\end{cases} \] 

(7)

Here, \( j \) is set of neighbor’s pixels present with the center pixel \( i \) in \( N_i \). In this clustering, appending of 2 with \( w_i \) is carried out to make the \( \varphi_{ij} \) as positive. \( N_i \) denotes the local cardinality. If \( x_i \) is brighter than \( \bar{x} \), \( \varphi_{ij} \) will be large i.e. \( 2 + w_i \) which implies that the pixel having higher VC with large \( w_i \) over the local window. Similarly, \( \varphi_{ij} = 2 - w_i \) if the average gray scale information \( \bar{x} \) is higher than the gray pixel \( x_i \). The algorithm behaves like a FCM when \( x_i = x_j \). The \( \varphi_{ij} \) is substituted in place of ‘a’ over every pixel in KFCM_S variant objective function to achieve the optimized cost function. Here the parameter \( \varphi_{ij} \) only based on the image pixel and the neighborhood pixel of an image. The modified KFCM_S variant constitutes adaptive contextual clustering and its cost function is

\[ J_{ACC} = 2 + \sum_{k \in N_i} \sum_{j \in N_j} u_{ik}^n (1 - K(x_i, v_{ij})) + \sum_{k \in N_i} \sum_{j \in N_j} \varphi_{ij} u_{ik}^n (1 - K(x_i, v_{ij})) \] 

(8)

The optimized cost function is realized with the membership and the center of the cluster.

3. RESULTS AND DISCUSSION

The main research work intention is to detect the malignancy of the high grade brain tumor especially, to diagnosis Glioblastoma tumor from other Astrocytoma brain tumor. Since the Glioblastoma tumor is a high grade malignant tumor and aggressive, it necessitates a special attention to diagnose it in earlier stage such that the mortality rate may be reduced. Here certain shape parameter constitutes the seven central moments derived from the moment invariant features which are used to diagnose the tumor region and dead cells. The detected features depict the shape feature of the tumor tissue and dead cells which effectively discriminating the Glioblastoma tumor from the malignant tumor. The optimized moment invariant feature is used to identify the shape of the tumor, such that the malignancy of Glioblastoma tumor can be easily distinguished. In image segmentation, the contextual information’s are used adaptively in clustering with respect to the local noise information such that the noises and outliers present in MR tumor image are removed efficiently and the precise and robust segmentation with improved accuracy is facilitated with all image details. Finally the boundary is formed by the Dilation operation from the formulated binary image by appending the image pixel. As a result cancerous cells and dead cells are easily diagnosed.

3.1. Performance Evaluation

The performance evaluation of the clustering module in the proposed system is investigated with segmentation accuracy and cluster validity measure in the detection of the abnormal brain image.

Segmentation quality

The clustering performances are analyzed with other traditional segmentation using accuracy is the ratio of the sum of the correctly segmented pixel to the sum of the total number of pixels in an image.

\[ SA = \frac{\sum_{i=1}^{n} A_i \cap C_i}{\sum_{i=1}^{n} C_i} \] 

(9)

Here the number of cluster is \( c \), pixels belongs to \( i^{th} \) class is \( A_i \). The pixels belongs to \( j^{th} \) class is \( C_j \) of segmented image.

Clustering performance

In validating the clustering performance, partition entropy and partition coefficients describe fuzziness of clustering, which are compared with various traditional methods. The partition
coefficient and the partition entropy are illustrated as

\[
C_{pc} = \frac{\sum_{i=1}^{N} \sum_{k=1}^{c} u_{ik}^2}{N}
\]

(10)

\[
C_{pe} = \frac{-\sum_{i=1}^{N} \sum_{k=1}^{c} [u_{ik} \log u_{ik}]}{N}
\]

(11)

In clustering performance analysis, better clustering is accomplished with minimum partition entropy and maximum partition coefficients. Since the partition entropy and coefficient only analyze the fuzzy partition, and it fails in measuring the featuring property, so, the Xie & Beni validity measure also considered which is described as

\[
C_{xb} = \frac{-\sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij} \left[ x_{ij} - v_{i} \right]^2}{N \left[ \min_{i \in c} \left[ \left| v_{i} - v_{i} \right|^2 \right] \right]}
\]

(12)

The improved clustering performance is realized when the image samples are accumulated within one cluster and distinguished among different cluster. Here, the malignant tumor is investigated with a cancerous region in the CSF cluster and the white matter cluster of Glioblastoma tumor influences the Necrosis (dead cells). In this tumor diagnosis, the validation of segmentation is demonstrated with the accuracy measurement in segmentation and measures of cluster validity. The segmentation performance investigated in Table 1 and Table 2 which overwhelms other segmentation approach in all aspects. The segmented cluster of malignant tumor illustrated in Fig. 3. The Necrosis (dead cells) with white matter and cancer cells with cerebrospinal fluid in Glioblastoma tumor is illustrated in Fig. 4.

Table 1 Clustering Performance with malignant brain tumor

<table>
<thead>
<tr>
<th>Clustering</th>
<th>Partition coefficient</th>
<th>Partition entropy</th>
<th>Xie measure Cxb</th>
<th>Clustering Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM</td>
<td>0.4294</td>
<td>0.1361</td>
<td>-23.01026</td>
<td>86.5</td>
</tr>
<tr>
<td>FCM_S</td>
<td>0.4377</td>
<td>0.0723</td>
<td>-752.575</td>
<td>88.5</td>
</tr>
<tr>
<td>KFCM</td>
<td>0.4791</td>
<td>0.03444</td>
<td>-13206</td>
<td>93.1</td>
</tr>
<tr>
<td>KFCM_S1</td>
<td>0.4810</td>
<td>0.02842</td>
<td>-14602.32</td>
<td>94.7</td>
</tr>
<tr>
<td>KFCM_S2</td>
<td>0.4897</td>
<td>0.02985</td>
<td>-15307.53</td>
<td>95.6</td>
</tr>
<tr>
<td>Proposed</td>
<td>0.7279</td>
<td>0.01133</td>
<td>-18463.61</td>
<td>98.2</td>
</tr>
</tbody>
</table>

Fig. 3. Clustering of malignant brain tumor (a) contrast enhanced T1-weighted image (b) White matter (c) Gray matter (d) CSF cluster (g) cancer cells (h) segmented tumor

Fig. 4. Clustering of Glioblastoma brain tumor (a) contrast enhanced T1-weighted image (b) White matter cluster (c) CSF cluster (d) cancer cells (e) Necrosis (f) detected Necrosis with the tumor tissue

The detected tumor tissue in malignant brain tumor and the Necrosis in Glioblastoma brain tumor illustrated in Fig. 3. and Fig. 4., and accuracy of segmentation is illustrated in Fig. 7. This effectively assist the radiologist and Neurosurgeons to diagnosis the malignancy of the high grade tumor. The clustering performances of malignant tumor and Glioblastoma brain tumor are illustrated in Table 1 and Table 2.
4. CONCLUSION
In this article, the automatic and efficient Glioblastoma brain tumor detection system was designed and implemented by the computer aided diagnosis (CAD) system. The analysis of the conventional approach in abnormal brain tumor detection inspired to implement the new diagnosing CAD module in distinguishing the higher malignancy of brain tumor. Seven shape features with moment invariant features were included with respect to the shape moment features which efficiently investigate the shape of Anaplastic Astrocytoma brain tumor and Necrosis with the Glioblastoma brain tumor. The cancerous cells present in Anaplastic Astrocytoma brain tumor and the Necrosis(dead cells) present in Glioblastoma brain tumor are well diagnosed with the clustered cerebrospinal fluid and white matter by automatic clustering approach. In detection of tumor tissue and Necrosis, after the conversion of clustered tumor and dead cells in to binary image, dilation operation well formulates the boundary of the detected cancerous cells and Necrosis. In Glioblastoma tumor analysis, the Necrosis size will guide the neurosurgeon in survival rate of the patient and further treatment plane as well as the necessary medication. The measured cluster validity and accuracy in segmentation interpreted the superiority of the proposed technique in contrast to the traditional tumor diagnosing systems.

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REFERENCES


