Statistical Features Segmentation Technique For MR Images Of Brain's Tumors

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Abstract

Medical image analysis has great significance in the field of treatment, especially in non-invasive and clinical studies. Medical imaging techniques and it analysis and diagnoses analysis tools enable the physicians and Radiologists to reach at a specific diagnosis. In this study, MR images have been used for discriminating the infected tissues from normal brain's tissues. A semi-automatic segmentation technique based on statistical futures has been introduced to segment the brain's MR image tissues. The proposed system used two stages for extracting the image texture features. The first stage is based on utilizing the 1st order statistical futures histogram based features such as (the mean, standard deviation, and image entropy) which is local in nature, while the second stage is based on utilizing the 2nd order statistical futures (i.e Co-Occurrence matrices features).

Similar coloring and semi-equal statistical features of the tumor area and the Gray Matter (GM) brain's tissue was the main encountered problem in the first presented segmentation method. To overcome this problem, an adaptive multi-stage segmentation technique is presented, in which the mean value of each pre-segmented classes has been used to distinguish the tumor tissue from others. The segmentation process is followed by a 2nd order classification method to assign image pixels accurately to their regions, using the invariant moments parameters weighted together with the Co-Occurrence parameters. Different samples of MR images for normal and abnormal brains (i.e. T1 and T2-weighted) have been tested, for different patients.

Keyword: MRI segmentation, brain tumors segmentation, co-occurrence matrices, invariant moments.

تقنية الانقسام باستخدام الخصائص الإحصائية لصور الرنين المغناطيسي لأورام الدماغ

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الخلاصة

إن لتحليل ومعالجة الصورةِ الطبيةِ أهميةٌ كبيرةٌ في مجال الطبِّ، خصوصاً في المعالجةِ غير المتدخّلةِ والدراساتِ السريريةِ. أن تقنياتُ التصوير الطبي, وأدواتِ التحليلِ والتشخيص المتعلقة بها ساعدت الأطباءَ واختصاصيي الأشعة من الوُصُول إلى التشخيص بشكل أفضل. في هذه الدراسة , تم استخدام صور الرنينِ المغناطيسي (MRI) ، لغرض الكشف عن الأنسجة المتضررة في الدماغ وتمييزها عن الأنسجة الغير متضررة. حيث تم استخدم تقنيات التقسيم الشبه الاوتماتيكية باستخدام الخصائص الإحصائية لغرض استخلاص تلك التفاصيل. الطريقة التي تم اقتراحها لهذا لغرض تتمثل بمرحلتين; الأولى تعتمد على استخدام الخصائص الإحصائية من الرتبة الأولى(مثل المعدل ومتوسط الانحراف المعياري والعشوائية).بينما المرحلة الثانية فتمثلت باستخدام الخصائص الإحصائية من الرتبة الثانية (مصفوفة التغايير).

إن التشابه اللوني وكذلك شبه التماثل بين معظم أنسجة الدماغ وخاصة بين المناطق المتضررة والمنطقة السنجابية (GM) هي من ابرز المشاكل التي واجهتنا في المرحلة الأولى من التقسيم. ولغرض التخلص من تلك المشكلة عمدنا إلى إجراء عملية تحسين لهذه المرحلة من خلال التعاقب في عملية التقسيم لقيم المعدل لكل صنف من الأصناف ولنفس المرحلة لغرض تمييز الورم عن باقي أنسجة الدماغ.المرحلة الثانية تمثلت باستخدام الخصائص الإحصائية من الرتبة الثانية بالاعتماد على نتائج المرحلة الأولى من التقسيم لغرض التصنيف الدقيق للورم. تم استخدام عينات مختلفة لشرائح صور الرنين المغناطيسي ولعدة أشخاص مصابين وأصحاء.

1. Introduction

Today, MRI is a valuable tool in medical diagnostic and treatment process. Magnetic Resonance Imaging "MRI", Computed Tomography "CT", Digital Mammography "DM", and other imaging modalities provide an effective means for noninvasively mapping the anatomy of a subject. These technologies have greatly increased knowledge of normal and unhealthy anatomy for medical research and are a critical component in diagnosis and treatment planning. One of the primary diagnostic and treatment evaluation tools for brain tumors is the MRI. It uses magnetic and radio waves, rather than X-rays, to produce a very detailed cross-sectional pictures. It becomes a widely used method for high quality medical imaging, especially in brain imaging. MRI can be used for estimating the size of the brain's tumor which useful in treatment process [1].

With the increasing size and number of medical images, the use of computers for facilitating their processing and analysis has become necessary. In particular, digital processing algorithms for the delineation of anatomical structures and other regions of interest become a key component in assisting and automating specific radiological tasks. These algorithms, called image (supervised and unsupervised) segmentation algorithms, play a vital role in numerous biomedical imaging applications; e.g. quantification of tissue volumes, diagnosis, localization of pathology, study of anatomical structure, treatment planning, partial volume correction of functional imaging data , and computer integrated surgery [2].

MRI brain's segmentation has played a critical role in these technical advancements. For any segmentation used in clinical applications, it is important to be of high precision and accuracy. There are many conventional digital supervised segmentation methods that can be used to differentiate between brain's tissues in MR images; e.g. region growing, edge detection, histogram based approaches, etc [2]. The problem with these methods is that; they need human interaction for accurate and reliable results. The human interaction is usually in the form of labeling the available image classes [3]. Many other segmentation methods segmenting image's regions having pixels with similar intensity values. Therefore, intensity inconsistencies produced by the non-homogeneity of the medical imaging modalities and biological variations of tissues are the goal of our presented segmentation methods. To solve this problem, several segmentation methodologies will presented, based on statistical and structural features. The automatic system that will be proposed in this paper can be regarded as an attempt to provide a complete automatic segmentation and labeling for differentiating the brain's tissues of interest; e.g. White Matter "WM", Gray Matter "GM", Cerebrospinal Fluid "CSF", and tumors.

2. Brain Tissues

Fig. (1) illustrates the main brain's tissues (GM, WM, and CSF), and four ventricles as connected cavities within the brain filled with the cerebrospinal fluid, each has the following duties, [4] [5]:

- **Gray matter:** forms the outer layer of the cortex, encasing the inner white matter almost completely, having gray color because of the high concentration of cell bodies.
- **White matter**: made up of nerve fibers that connects different parts of the cortex, and the cortex with other parts of the brain. These are white because of the high concentration of axons.
- **Cerebrospinal Fluid (CSF):** It is a clear substance that circulates through the brain and spinal cord. It provides nutrients and serves to cushion the brain and, therefore, protects it from injury. As this fluid gets absorbed, more is produced from the choroids plexus, a structure located in the ventricles. A brain tumor can cause a build-up or blockage of CSF.

• **Tumor and Edema:** For abnormal brain [shown in right side of fig.(1)], two more tissues are existed; i.e. tumor and edema tissue. A tumor is an abnormal growth of tissue. Unlike tumor structures, there is no spatial prior for the edema. As a consequence, the probability density function for edema cannot be defined automatically; i.e. white matter and edema would result in similar probability density functions [4] [5].

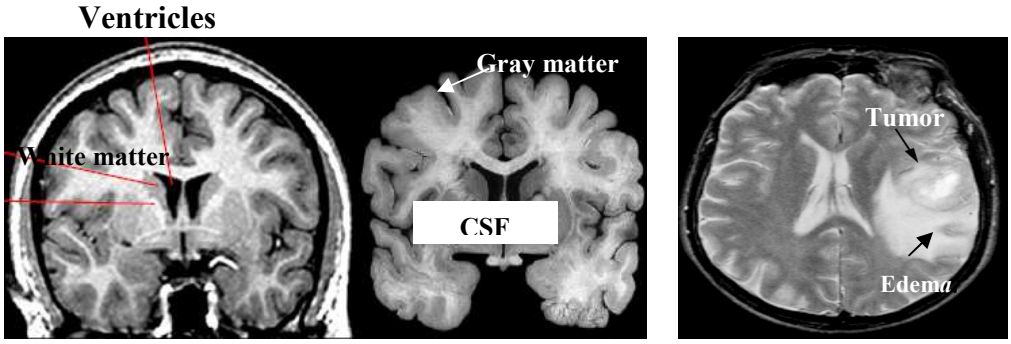


Figure 1- The Main Brain's Tissues, For Normal (Lefts) And Abnormal (Right) Brains, [4].

3. Image Analysis Systems

Generally, image analyzing systems involve the operations illustrated in fig.(2). The Preprocessing improves the quality of the data by reducing the existed artifacts, while the Feature Extraction and Selection provides the measurement to facilitate the image segmentation process. Finally, image Segmentation and Classification group pixels into regions and define the boundaries of the various regions [6] [7]:

Image segmentation is a crucial step toward image interpretation, since the rest of the analysis fully relies on the data from this step. Subsequent, medical processing and analysis steps may include quantification, registration, visualization and computer aided diagnosis. Therefore, image segmentation is one of the most important tasks in computer vision and image processing, [8][9], it can be performed either manually or using certain image processing and computer vision techniques. Generally, image segmentation techniques locate objects consisting pixels having something in common; e.g. having similar intensity values or same colors , [10] [11]. In this paper, both statistical and structural features will be used to segmenting normal or/and abnormal brain's tissues.

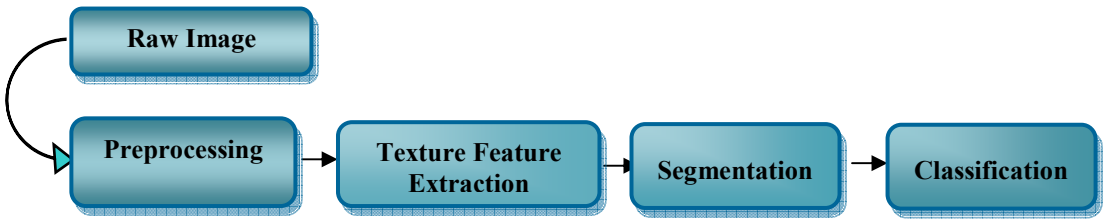


Figure 2- Major Steps Of Image Analysis System [7]

4. Feature Extraction

The transformation of an image into set of features is known as feature extraction. In the literature, different approaches have been proposed to extract the suitable sets of features; e.g. statistical-based approach, structural-based approach, model-based approach, and transform-based approach, [12] [13].In this paper, we shall concentrate on the statistical-based approach, using the 1st and 2nd order statistics, to identify abnormalities on tissues of the T1 and T2-weighted brain's MRIs.

4.1 Statistical Features Analysis

A statistical feature is one of the well known and simplest methods, so far used, to measure the image texture behaviors. Normally, image analysis systems used two methods for extracting the image texture features; i.e. utilizing either 1st order histogram features, the 2nd order of the co-occurrence matrix features, or

utilizing higher order of invariant moments features.

4.1.1 First-order Histogram Based features

Histogram summarizes the statistical information about the image. For an image f(x, y) of dimensions N×M and G-gray values, its histogram (referred as probability density function "pdf ") is presented by, [14];

$$\rho(z_i)=\frac{n(z_i)}{M\times N}\quad,\quad z_i=0,1,.....G\text{-}1 \qquad (1)$$

The probability function $\rho(z_i)$ of occurrence of the intensity level z_i is obtained by dividing the number of the intensity level $n(z_i)$ by the total number of pixels in the image.

Quantitatively, there are certain useful features can be obtained from the image's histogram [15] e.g.

a. **The image Mean value**:

$$\mu = \sum_{i=0}^{G-1} z_i \rho(z_i) \qquad (2)$$

b. The image Variance value:

$$\sigma^2 = \sum_{i}^{G-1} (z_i-\mu)^2 \rho(i) \qquad (3)$$

c. The image Entropy value:

$$H = -\sum_{z_i=0}^{G-1} \rho(z_i)\log\ \rho(z_i) \qquad (4)$$

4.1.2 Co-Occurrence Matrix based Features

It has been shown above, the 1st order histogram based features are local in nature; i.e. they haven't reflected any spatial information. For this purpose, the gray-level spatial co-occurrence matrices have been designed to represent 2nd order histogram features based on the joint probability distribution of pairs of pixels, separated by distance "r" at an angle "θ" (usually r =1,2,.., and θ=0°,45°, 90°, 135°). As an example, let a pair of pixels f(i, j) and f(m, n) in an image, separated by distance "r" at an angle "θ" with respect to the horizontal axis. The two-dimensional histogram can be estimated by the joint probability distribution function, given by;

$$P(a,b,i,j,m,n,r,\theta)\approx P_r\{f(i,j)=a, f(m,n)=b\} \qquad (5)$$

Where: a & b represent image intensity values over the range $0\le a,b\le G-1$.

For each parameter set $(a,b;i,j,m,n;r,\theta)$, the two-dimensional histogram can be regarded as a G×G array of members relating the measured statistical dependency of pairs of pixels (named the Co-Occurrence matrix), for the details see [17] [18]. It is often convenient to normalize the co-occurrence matrices so that they approximate discrete joint probability distribution of co-occurring gray-levels. This is accomplished by dividing each entry in the matrix by the total number of paired occurrences, for certain separating distance at certain angle "$N_{r,\theta}$ ", i.e.

$$\rho_{r,\theta}=\frac{1}{N_{r,\theta}}P_r\{f(i,j)=a, f(m,n)=b\} \qquad (6)$$

Haralick et al [17] have proposed a variety of measures that can be employed to extract useful textural information from "$\rho_{r,\theta}$ " matrices. Three of these 2nd order measures have been adopted in this research and used to differentiate between Brain's tissues, i.e.

a. **Moment of Inertia**: Measures the local contrast of an image:

$$INR = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-j)^2 \rho_{r,\theta}(i,j) \qquad (7)$$

b. **Local Homogeneity**: Measures the degree of homogeneity through image values, given by;

$$LOCH=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{\rho_{r,\theta}(i,j)}{1+(i-j)^2} \qquad (8)$$

c. Correlation: represents the relationship between image's values:

$$Cor=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{(i-\mu_x)(j-\mu_y)\rho_{r,\theta}(i,j)}{\sigma_x\sigma_y} \qquad (9)$$

Where: μ_x, μ_y, and σ_x, σ_y are the rows and columns means and standard deviations.

4.1.3 Invariant Moments

Other higher order statistical measures have also, being adopted and used in this paper; i.e. the Invariant Moments have been suggested by Hu [20] to measure the similarity between image regions. They provide an analytical method to characterize both statistical and structural texture. Given a two-dimensional continuous function f(x, y), the (p + q) order moment is defined by [21];

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)dxdy \qquad (10)$$

For a 2D digital image f(x, y), the central moments can be expressed by [21]:

$$\mu_{pq}=\sum_x\sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y) \qquad (11)$$

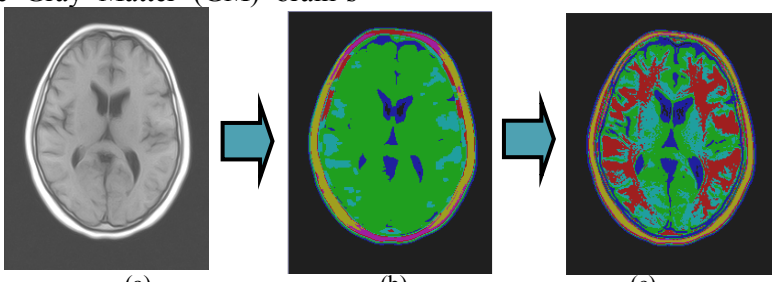
From the 2nd and 3rd order moments, a set of **seven invariant moments** have been derived and used to measure the degree of similarities between various image regions. For the details, see Gonzalez and Wintz [21].

5. The Proposed Methods

In this paper, several automatic and semi-automatic supervised and unsupervised segmentation methods have been suggested and used for isolating the Brain's tumor from the healthy tissues. The methods, as will be illustrated, are based on utilizing the first and higher orders features.

5.1 Two-Stage Unsupervised-Supervised Segmentation Method

This segmentation method includes two stages; in the first stage the 1st order statistical features (i.e. Mean, Variance, and Entropy) have been computed within certain defined window's size. Since the extracted statistical features, in this stage, depends mainly on the image intensity values, the resulted segmented (or classified) image [see Fig. 3b] hasn't recognized the Tumor's from the Gray Matter (GM) brain's tissue. To overcome this problem, a second stage segmentation operation is proposed to refining the result of the preliminary classification/segmentation process. In this stage, the mean values of the preliminary classes are computed (using the pixel's values of the original image), then a reclassification operation is performed by assigning each classified point to its nearest mean value, illustrated in Fig. 3c. In fact, the second stage classification could be regarded as to be supervised classification process, because it has been performed on initially classified image points. It is remained to be noted that; the nearness measure between the counted means and the preliminary classified image pixels is performed using the minimum distance criterion [22].



(a) Original T1-Weighted MR Image (b) Preliminary Classified Image (c) Final 2nd Stage Classified Image

Figure 3- Multi-Stage Unsupervised-Supervised Segmentation Method.

5.2 Tumor Isolation Using 2nd Order Supervised Statistical Method

For more efficient result, the two-stage segmented image can be processed again by utilizing higher order statistical features. The co-occurrence matrices and the seven invariant moments have been used to isolate the tumor tissue from the surrounded contain of the brain. Different samples of MRIs for normal and abnormal brains (T1and T2 weighted) have been tested. The refining operation by this method can be summarized by the following steps:

Step1: Input the original and the two-stage classified images;

Step2: Select number of points, classified as to be tumor tissue by the two-stage method;

Step3: Compute the 2nd order co-occurrence and the seven invariant moment features, using suitable predefined window's size.

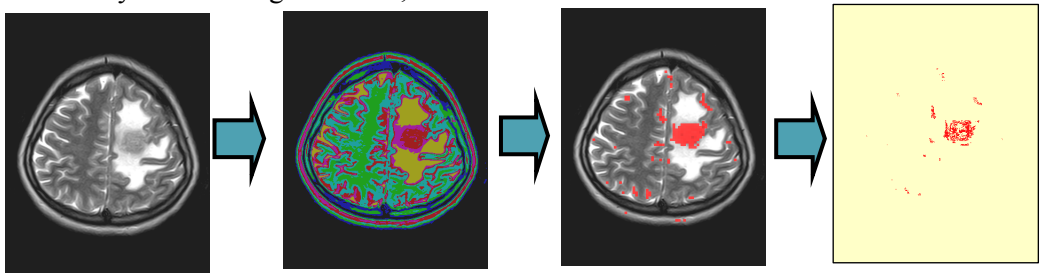
Step4: If the **Minimum Deviated Distance (MDD**) between the window's features and the closest features of the selected points was less than a decided

Threshold (Th), then the window's center point is decided as to be tumor point, otherwise;

Step 5: The window's center is decided as to be non-tumor.

Step 6: Continue till the end of the image.

The above mentioned tumor isolation process is illustrated in Fig. 4 below;



Original Abnormal T2-Weighted MRI | Two-Stage (7-Classes) Classified Image Classified Image | Defining Only Tumor Points From The And Invariant Moment | Isolating Tumor Using Co-Occurrence

Figure 4- Refining Results Using The Co-Occurrence And Invariant Moment Features.

6. Results and Discussions

As it has been discussed above, the unsupervised segmentation method requires priory defining; number of classes, window's size and minimum deviated distance "MDD". Figure (5) represents different classified images, obtained by utilizing 3×3 windows, **MDD** = 12, and various number of decided classes. The method has been applied on both normal and abnormal brain images. As it is obvious, the preferable number of classes ranges between 5-to-9, which represents the main brain's tissues. The **MDD=12** is decided due to the gained results through our present course of work. The main advantage acquired from the implementation of the unsupervised classification is that; numbers of regions are defined priory by the operators. For abnormal brains, number of regions should be, at least, increased by one of the normal brain tissues. For best differentiation between normal and abnormal MRI brains, the results showed that number of decided classes should be 7 classes.

The co-occurrence matrices and the 7-invariant moments have been used to isolate the tumor tissue from the surrounded contained of the brain. By defining, only tumor points from the classified image using suitable predefined window's size. If "MDD" between the window's features and the closest features of the selected points was less than a decided "Th" then the window's center point is decided as to be tumor point, otherwise; the window's center is decided as to be non-tumor. Figure (6) represents different classified images, obtained by utilizing 3×3 windows, MDD=12, and different threshold values.

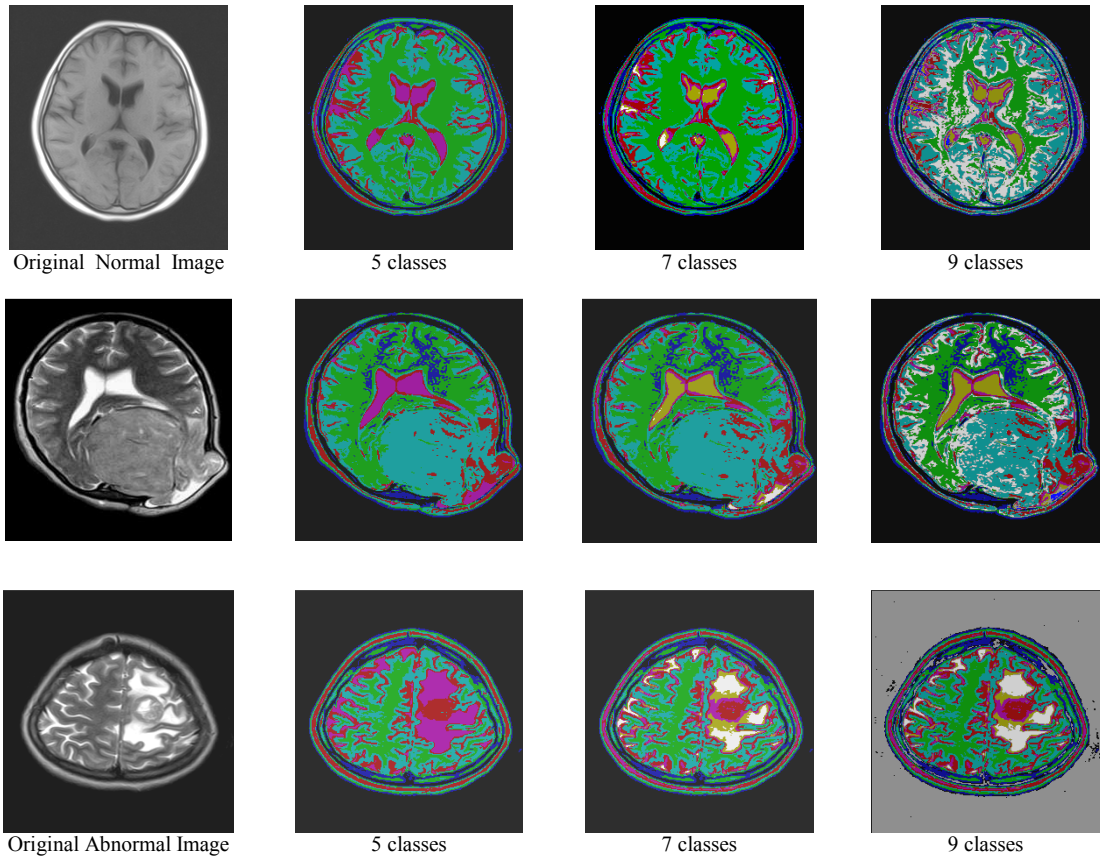


Figure 5- Unsupervised Classification Results For Normal And Abnormal T2-Weighted MRI, Using Different Number Of Classes, 3×3 Window's Size And MDD = 12.

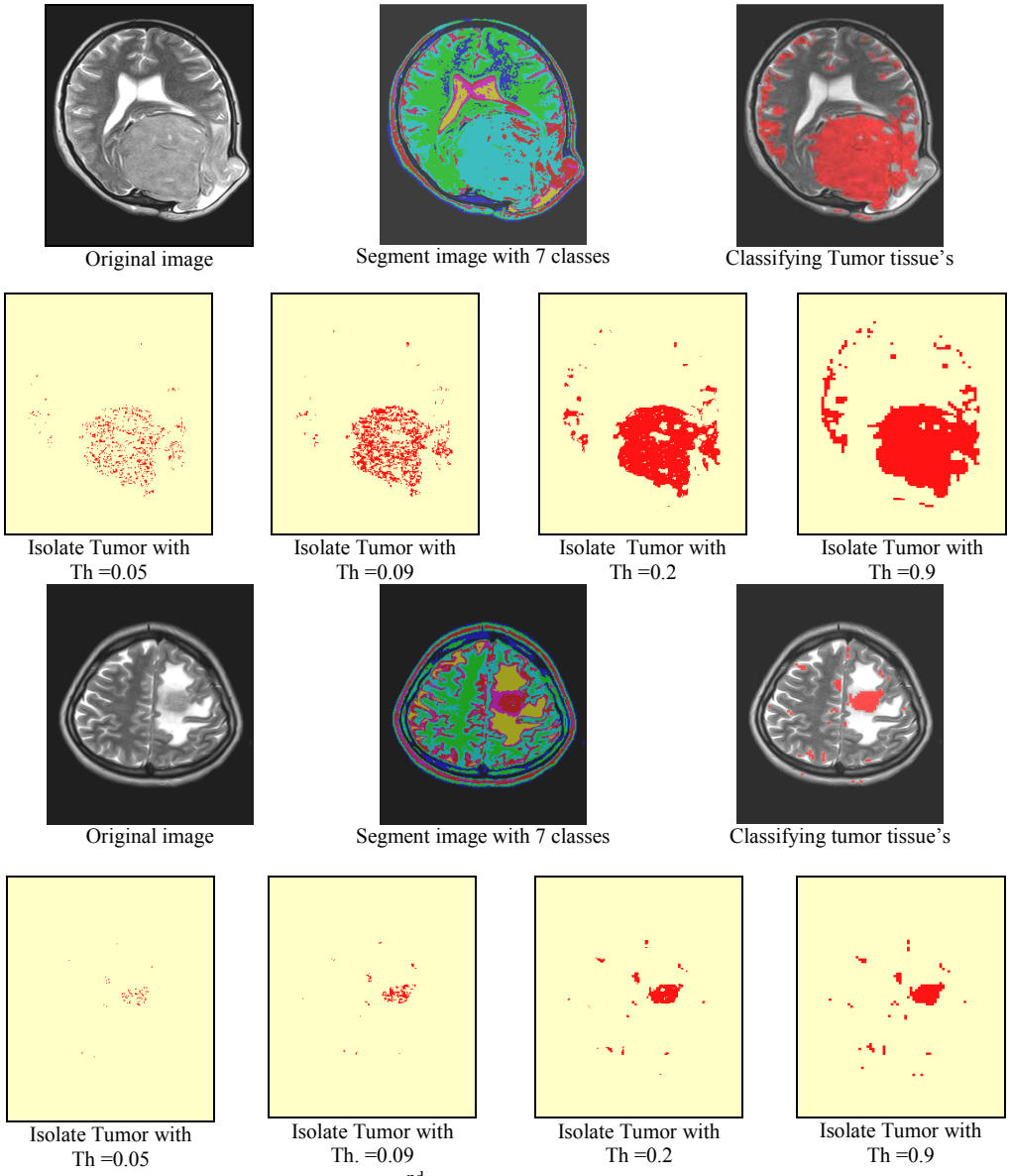


Figure 6- The Isolate Tumor Tissues Using 2nd Order Statistical Feature, From Axial T2-Wieghted Abnormal MR Images With Different Threshold Values.

7. Conclusions

The problems that are usually encountered when trying to design an automatic system for tumor's detection system is that; a large number of tumor's types are existed; i.e. differs in size, shape, location, tissue composition and homogeneity. Therefore, the semi-automatic-unsupervised segmentation technique introduced in this paper was failed because it is based on the intensity information in an image; i.e. the color overlapping problem restricted the isolation of the tumor from the gar matter brain's tissue. To improve the results, an adaptive multi-stage segmentation method is proposed to classify pre-segmented classes and extracting the tumor tissue from those showed similar behaviors. The co-occurrence and the invariant moments which regarded as higher orders statistical features have been proposed and presented to enhance the differentiation process. Our opinion is that, the successive-stages of unsupervised features can be regarded as be more successful for recognizing, identifying, and isolating tumor tissue in MR images

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