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Brain Tumor Detection Using Adaptive K-Means Clustering Segmentation

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Abstract - *Magnetic resonance imaging (MRI) is widely preferred technique to access the Brain tumor, But Due to large amount of data produced by MRI prevents manual segmentation in a reasonable time. So, efficient segmentation methods are required for MRI Brain tumor detection. The watershed transform has interesting property and is popular that make it useful for many segmentation application. The drawback associated with watershed transform is the over segmentation which results in MRI brain image. In this paper an adaptive K-Means clustering algorithm is used for detection of brain tumor on segmentation and morphological operator. The proposed method allows the segmentation of tumor tissues with accuracy compared to manual segmentation. The quantitative and visual segmentation result shows the superiority of the proposed method.*

Keywords-— *MRI, Brain Tumor, image segmentation, Watershed, K-Means Clustering*

I. INTRODUCTION

In medical imaging, segmentation of tissues and systems plays an vital position in lots of image analysis programs evolved for scientific analysis [1]. Image segmentation allows in prognosis of brain sicknesses and enables in quantitative evaluation of MR Images such as measuring accurate size and area of extracted portion. Exact measurements in brain diagnosis are difficult because of different shapes and sizes of tumor [2, 3]. The K-means algorithm implements a divisive clustering and was first mentioned by means of Duda and Hart . Treatment plans and assessment of disorder development of that ailment affect particular tissues or structures, lead to loss and abnormalities. An accurate, dependable, and automated segmentation of those tissues and structures can enhance diagnosis and remedy of mind diseases [4,5]. Manual segmentation is bias and generally accurate but is impractical for large datasets because it is tedious and time consuming. Automatic segmentation techniques can be beneficial for scientific packages if they have capacity to segment like an expert, extremely good performance for diverse datasets and affordable processing velocity for massive datasets because it's miles tedious and time Consuming [6, 7] Brain tumor is one of the important reasons for increasing mortality among youngsters and adults. A tumor is a neoplasm that is formed by means of an extraordinary increase of cells. Brain tumors can be separated into popular classes depending at the tumors origin, their growth pattern and malignancy. Tumors that get up from cells inside the mind or from the covering of the brain are called primary brain tumors. Tumors arise while cancer cells spread to the brain from a primary most cancers in any other part of the body are called secondary brain tumors. It has been concluded from the research factor of view that the quantity of people suffering and death from brain tumors has been elevated perhaps as a whole lot as three hundred over beyond 3 a long time. The exceptional form of imaging to diagnose most forms of brain tumors is MRI [8, 9]. This technique is basically used to discover the variations in the tissues which have a far better approach in comparison to computed tomography. So this makes this method a completely unique one for the brain tumor extraction. In this paper we propose an improvement to the K-Means clustering for correctly detecting the location of brain tumor in MR images.

Segmentation is an important process in most medical Image evaluation and classification for radiological assessment or computer-aided [12] diagnosis. Basically, image segmentation strategies can be categorized into 3 classes: edge - based methods, region-based methods [10], and pixel-based techniques. K-method clustering is a key approach in pixel-based techniques. Because pixel-based methods based on K-Means clustering are simple and the computational complexity is surprisingly low as compared with other region-based or edge-based methods, the application is more practicable. Furthermore, K-manner clustering is appropriate for biomedical image segmentation because the wide variety of clusters is. normally recognized for images of particular areas of the human anatomy. Many researchers have proposed associated studies into K-Means clustering segmentation [10,14]. The improvements accomplished by means of [10,14] have been remarkable, however extra computational complexity and extra software functionality are required. In this paper, carefully select the right features from brain images as the clustering features to achieve good segmentation effects while preserving the low computation aspect of the segmentation algorithm. Because the colour space transformation function in our proposed method is a essential operation for most image processing systems, the color-space translation does not cause extra overhead within the proposed scheme. Therefore, by using the use of color-based segmentation with K-Means clustering to magnetic resonance (MR) brain tumors, the proposed image tracking technique keeps efficiency. The experimental consequences additionally confirm that the proposed method facilitates pathologists distinguish specific lesion sizes and areas.

This research paper is organized as follows. In Section II, the proposed K-Means clustering is described. Performance metrics in section-III.Experimental results and comparison with existing extraction algorithms are presented in Section IV. Finally, conclusions come in Section V.

II. PROPOSED SYSTEM

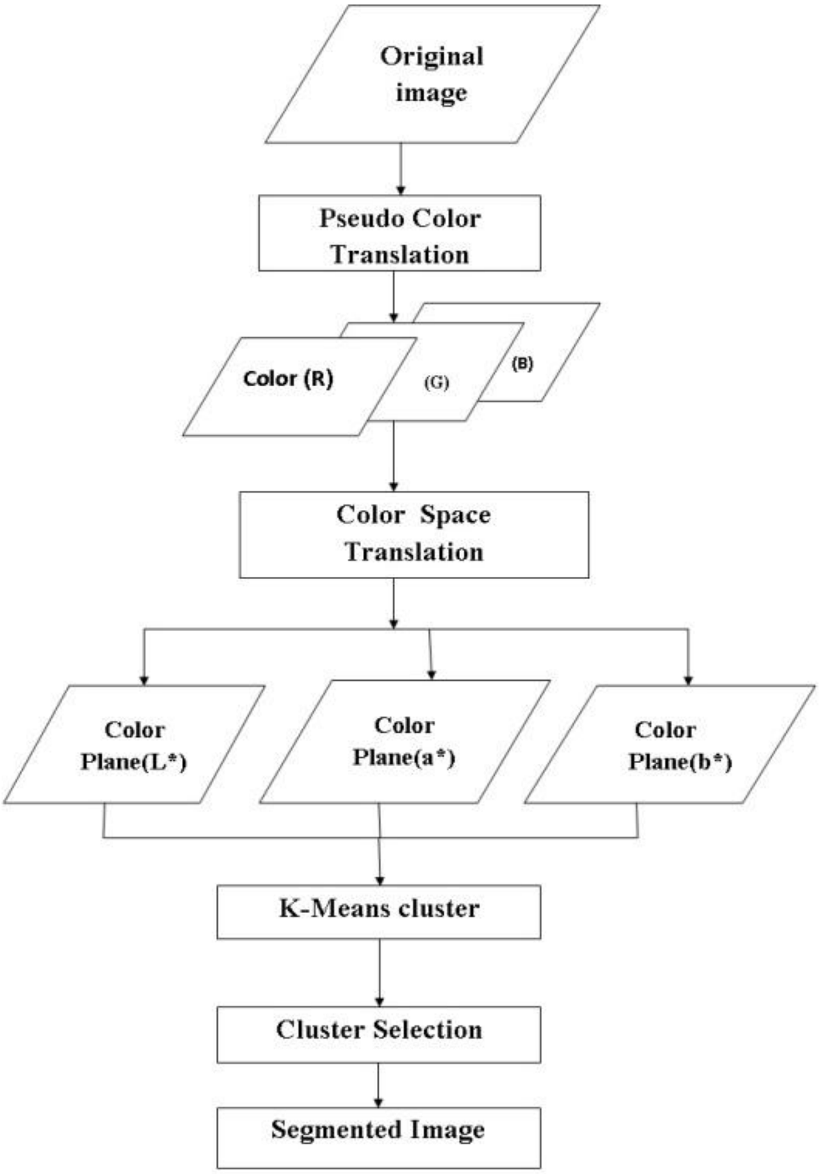

Fig.1 Block diagram of proposed method

Basically, feature space selection is a key issue in K-means clustering segmentation. The original MR brain image is rendered as a gray-level image that is inadequate to support fine features. To obtain improved fine details with prominent edges and enhance the visual density, the proposed method applies pseudo-color transformation, a mapping function that maps a gray-level pixel to a color-level pixel by a lookup table in a predefined color map. An RGB color map contains R, G, and B values for each item. Each gray value maps to an RGB item. The proposed method has adopted the standard RGB color map, which gradually maps gray-level values 0 to 255 into blue-to-green-to-red color. To retrieve important features to benefit the clustering process, the RGB color space is further converted to a CIE Lab color model ($L^*a^*b^*$) [11]. The $L^*a^*b^*$ space consists of a luminosity layer L^*, a chromaticity-layer a^*, which shows where color falls along the red-green axis, and a chromaticity-layer b^*, which indicates where the color falls along the blue-yellow axis. The translating formula calculates the tri-stimulus coefficients first as

$$W=0.4303R+0.3461G+0.1784B,$$
$$Y=0.2219R+0.7068G+0.0713B,$$
$$Z=0.0202R+0.1296G+0.9393B \quad (1)$$

The CIE Lab color model is calculated as

$$L^{*}=116\left(h\left(\frac{y}{y_s}\right)\right) -16,$$
$$1a^{*}=500\left(h\left(\frac{w}{w_s}\right)-h\left(\frac{y}{y_s}\right)\right), \quad (2)$$
$$b^{*}=200\left(h\left(\frac{y}{y_s}\right)-h\left(\frac{z}{z_s}\right)\right),$$
$$h(q)=\begin{cases} 3\sqrt{q} & q>0.00856 \\ 7.787q+\frac{16}{116} & q\le 0.008856 \end{cases}$$

where Y_s, Ws, and Zs are the standard stimulus coefficients. Both the a* and b* layers contain all required color information. Therefore, the proposed method then classifies the color in the a*b* space using K-means clustering. K-means is a widely used clustering algorithm to partition data into k clusters. Clustering is the process for grouping data points with similar feature vectors into a single cluster and for grouping data points with dissimilar feature vectors into different clusters. Let the feature vectors derived from l clustered data be $X = \{xi \mid i= 1,2...,l\}$ .The generalized algorithm initiates k cluster centroids $C = \{c\,j \mid j=1,2,...,k\}$ by randomly selecting k feature vectors from X. Later, the feature vectors are grouped into k clusters using a selected distance measure such as Euclidean distance so that

$$d = \|xi - c\,j\|. \quad (3)$$

The next step is to recomputed the cluster centroids based on their group members and then regroup the feature vectors according to the new cluster centroids. The clustering procedure stops only when all cluster centroids tend to converge. After the clustering process, the cluster containing an area of interest is selected as the primary segment.

III. PERFORMANCE METRICS

The evaluation of segmentation performance is also carried out quantitatively by employing volume metrics namely, sensitivity, specificity, Accuracy[15–17]. Sensitivity is defined as the number of the true positives divided by the total number of elements that belong to the positive cluster

$$\text{Sensitivity (True positive rate)} = \frac{TP}{(TP+FN)} \quad (4)$$

$$\text{Specificity (False positive rate)} = \frac{TN}{TN+FN} \quad (5)$$

$$\text{Accuracy(Percent of all samples correctly classified)} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (6)$$

Where , TP(True Positives): Is the correctly classified positive cases.
FN(False Negatives): Is the correctly classified negative cases,
FP (False Positives): Is the incorrectly classified negative cases and
FN (False Negative): Is the incorrectly classified positive cases

IV. EXPERIMENTAL RESULTS

In this section, the results of our proposed image segmentation technique obtained using real MRI brain image were shown. In order to validate result the proposed segmentation algorithm was experimented on MATLAB R2014a software.

To demonstrate the detection performance of the proposed method, an MR brain image (288×288) containing the pathological change area shown in Fig. 2(a) was considered as a test image. The RGB color image converted from the gray-level image is shown in Fig. 2(b).

To Show that the feature vectors proposed in our method really can provide better segmentation performance, two different data sets were prepared: the gray feature vectors of the original MR brain image and the RGB features derived from the converted RGB color image. Generally, an MR brain image consists of regions that represent the bone, soft tissue, fat and background. In these two different data sources, visual judgments from the gray and color test images suggest three primary clusters in the test image shown in Fig. 2(a) when k=3. Figs. 2(c)–(d) show the image labelled by cluster index from the K-means process for different kinds of feature vectors. Using index labels, we can separate objects in the brain image by three colors: white, gray, and black. The final segmentation results generated by K-Means clustering are shown in Figs. 2(e). By combining Fig. 2(c) and Fig. 2(d), we can see that not only a tumor (in the right half of the image) is identified but also the white matter, cerebrospinal fluid, and the ventricles are. In other words, the segmentation result cannot exactly identify the position of the tumor shown in Fig. 2(d). The same phenomenon exists in Fig. 2(e). However, the segmentation result generated by the proposed method can ignore most of the white matter, cerebrospinal fluid, and ventricles while exactly locating the position of the tumor. Therefore, the segmentation quantitative performance of the proposed features derived from the CIE Lab color model was shown in Table 1.

Table.I: Comparision of performance metrics of existing and proposed method

Method	True positive	False Negaive	True Negative	False Positive	sensitivity	specificity	Accuracy	Time Period (in sec)
Watershed transform	0.87	0.56	15.52	0.15	0.61	0.96	95.84	9.73sec
Proposed Method	0.95	0.59	16.42	0.16	0.62	0.96	95.86	0.216sec

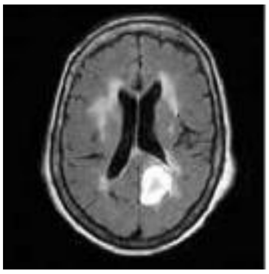

Fig2 (a) gray-level image

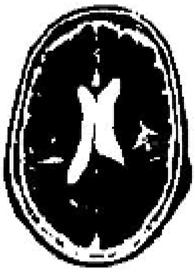

Fig2 (b) image Labeled by Cluster index

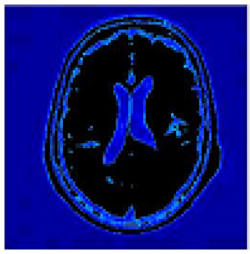

Fig2 (c) Objects in Cluster 1

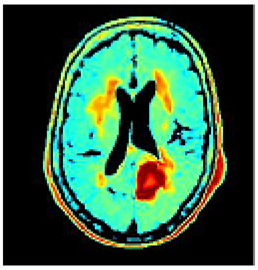

Fig2 (c) Objects in Cluster 2

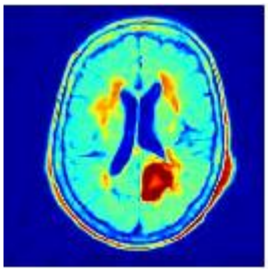

Fig2 (d) Objects in Cluster 3

Fig2 (e) Final Segmented image

V. Conclusion

In this paper a tumor segmented method which Uses Adaptive K-Means clustering method . The proposed system determines the initial cluster k value to minimize the execution time. The performance valuation of the proposed technique, its minimization time strategy, and its quality has been demonstrated.. The results obtained are quantitatively verified with other existing method shows that our approach provides better result.

. In future work, the 3D evaluation of the brain tumor detection using 3D slicer will be carried out. As well as to increase the efficiency of the segmentation process, an intensity adjustment process will provide more challenging and may allow us to refine our segmentation techniques tothe MRI brain tumor segmentation

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