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RESEARCH ARTICLE

Efficient Texture Segmentation by Hierarchical Multiple Markov Chain Model

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Abstract— A novel multiscale texture model and a related algorithm for the unsupervised segmentation of medical images to locate tumors are proposed in this project. Elementary textures are characterized by their spatial interactions with neighboring regions along selected directions. Such interactions are modeled, in turn, by means of a set of Markov chains, one for each direction, whose parameters are collected in a feature vector that synthetically describes the texture. Based on the feature vectors, the texture are then recursively merged, giving rise to larger and more complex textures, which appear at different scales of observation: accordingly, the model is named Hierarchical Multiple Markov Chain (H-MMC). The Texture Fragmentation and Reconstruction (TFR) algorithm, addresses the unsupervised segmentation problem based on the H-MMC model. The "fragmentation" step allows one to find the elementary textures of the model, while the "reconstruction" step defines the hierarchical image segmentation based on a probabilistic measure which takes into account both region scale and inter-region interactions. The proposed algorithm provides robust and fast segmentation when compared to other algorithm and this project is used in medical science to trace the tumor.

Keywords- Hierarchical Multiple Markov Chain, Hierarchical Model, Texture Fragmentation and Reconstruction

I. INTRODUCTION

The techniques of digital image processing have found a myriad of applications in diverse fields of scientific, commercial, and technical endeavor. Image processing education therefore needs to cater to a wide spectrum of people coming from different educational backgrounds. Digital Image Processing (DIP) is a multidisciplinary science that borrows principles from diverse fields such as optics, surface physics, visual psychophysics, computer science and mathematics. The many applications of image processing include: astronomy, ultrasonic imaging, remote sensing, video communications and microscopy, among innumerable others. Common Steps in image processing is illustrated in Figure 1.1

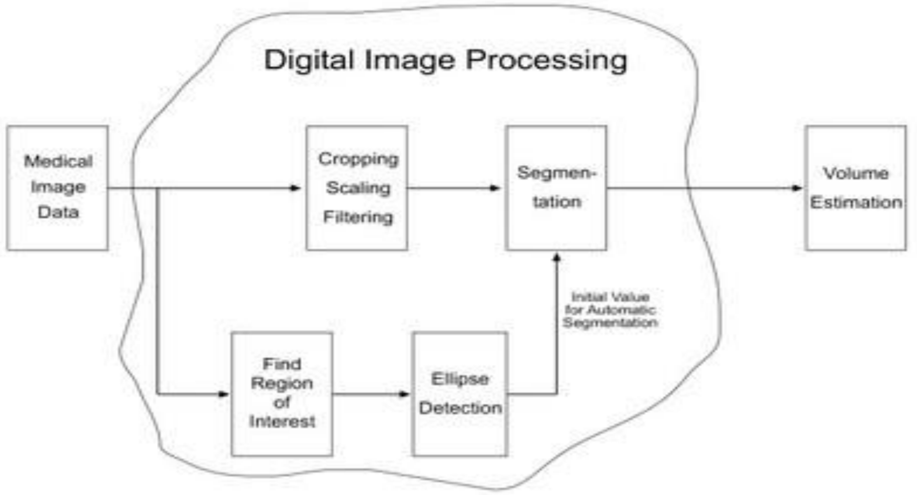

Figure 1.1 Common Steps in image processing

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analog image processing; it allows a much wider range of algorithms to be applied to the input data, and can avoid problems such as the build-up of noise and signal distortion during processing. Digital image processing allows one to enhance image features of interest while attenuating detail irrelevant to a given application, and then extract useful information about the scene from the enhanced image. In electrical engineering and computer science, image processing is any form of signal processing for which the input is an image, such as photographs or frames of video; the output of image processing can be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing are also possible. This article is about general techniques that apply to all of them. The acquisition of images is referred to as imaging.

II. RELATED WORK

P. Andrey et al [1] propose an evolutionary approach, selectionist relaxation as a solution to the problem of segmenting Markov random field modeled textures in unsupervised mode. In selectionist relaxation, the computation is distributed among a population of units that iteratively evolves according to simple and local evolutionary rules. A unit is an association between a label and a texture parameter vector. The units whose likelihood is high are allowed to spread over the image and to replace the units that receive lower support from the data. Consequently, some labels are growing while others are eliminated. Starting with an initial random population, this evolutionary process eventually results in a stable labelization of the image, which is taken as the segmentation. In this work, the generalized Ising model is used to represent textured data. Because of the awkward nature of the partition function in this model, a high-temperature approximation is introduced to allow the evaluation of unit likelihoods.

Thomas Brox et al [2] propose the popularity of level sets for segmentation is mainly based on the sound and convenient treatment of regions and their boundaries. Unfortunately, this convenience is so far not known from level set methods when applied to images with more than two regions. This communication introduces a comparatively simple way how to extend active contours to multiple regions keeping the familiar quality of the two-phase case. We further suggest a strategy to determine the optimum number of regions as well as initializations for the contours.

David A. Clausi et al [3] propose design-based method to fuse Gabor filter and grey level co-occurrence probability (GLCP) features for improved texture recognition is presented. The fused feature set utilizes both the Gabor filter's capability of accurately capturing lower and mid-frequency texture information and the GLCP's capability in texture information relevant to higher frequency components. Evaluation methods include comparing feature space separability and comparing image segmentation classification rates. The fused feature sets are demonstrated to produce higher feature space separations, as well as higher segmentation accuracies relative to the individual feature sets. Fused feature sets also outperform individual feature sets for noisy images, across different noise magnitudes. The curse of dimensionality is demonstrated not to affect segmentation using the proposed the 48-dimensional fused feature set. Gabor magnitude responses produce higher segmentation accuracies than linearly normalized Gabor magnitude responses. Feature reduction using principal component analysis is acceptable for maintaining the segmentation performance, but feature reduction using the feature contrast method dramatically reduced the segmentation accuracy.

Ciro D'Elia et al [4] propose a new image segmentation algorithm based on a tree-structured binary MRF model. The image is recursively segmented in smaller and smaller regions until a stopping condition, local to each region, is met. Each elementary binary segmentation is obtained as the solution of a MAP estimation problem, with the region prior modeled as an MRF. Since only binary fields are used, and thanks to the tree structure, the algorithm is quite fast, and allows one to address the cluster validation problem in a seamless way. In addition, all field parameters are estimated locally, allowing for some spatial adaptivity. To improve segmentation accuracy, a split-and-merge procedure is also developed and a spatially adaptive MRF model is used.

Numerical experiments on multispectral images show that the proposed algorithm is much faster than a similar reference algorithm based on "flat" MRF models, and its performance, in terms of segmentation accuracy and map smoothness, is comparable or even superior.

III. PROJECT DESCRIPTION

Image segmentation is a low-level processing of critical importance for many applications in such diverse domains as medical imaging, security, remote sensing, industrial automation, and many others. Although it has been widely studied in recent decades, in many cases, it still remains an open problem, as is the case of textured images where the spatial interactions may cover long ranges, asking for complex high order modeling. The situation is especially critical in the unsupervised case since no prior information is given and the process is completely blind. Segmentation is the fundamental process which affects the overall performance of any automated image analysis system. Image regions, homogeneous with respect to some usually textural or color measure, which result from a segmentation algorithm are analyzed in subsequent interpretation steps.

Texture-based image segmentation is area of intense research activity in recent years and many algorithms were published in consequence of all this effort. These methods are usually categorized as region-based, boundary-based, or as a hybrid of the two. Different published methods are difficult to compare because of lack of a comprehensive analysis together with accessible experimental data, however available results indicate that the ill-defined texture segmentation problem is still far from being satisfactorily solved. Spatial interaction models and especially Markov random fields-based models are increasingly popular for texture representation. Several researchers dealt with the difficult problem of unsupervised segmentation using these models which is also addressed in this paper.

Image segmentation is an important and challenging factor in the medical image segmentation. A novel multiscale texture model and a related algorithm for the unsupervised segmentation of medical images to locate tumors are proposed in this project. Elementary textures are characterized by their spatial interactions with neighboring regions along selected directions. Such interactions are modeled, in turn, by means of a set of Markov chains, one for each direction, whose parameters are collected in a feature vector that synthetically describes the texture. Based on the feature vectors, the texture are then recursively merged, giving rise to larger and more complex textures, which appear at different scales of observation: accordingly, the model is named Hierarchical Multiple Markov Chain (H-MMC). The Texture Fragmentation and Reconstruction (TFR) algorithm, addresses the unsupervised segmentation problem based on the H-MMC model. The "fragmentation" step allows one to find the elementary textures of the model, while the "reconstruction" step defines the hierarchical image segmentation based on a probabilistic measure (texture score) which takes into account both region scale and inter-region interactions.

3.1 Image Acquisition

Images of a patient obtained by MRI scan is displayed as an array of pixels (a two dimensional unit based on the matrix size and the field of view) and stored in MATLAB 7.0. Here, grayscale or intensity images are displayed of default size 256 × 256. The following figure displayed a MRI brain image obtained in Mat lab 7.0. A grayscale image can be specified by giving a large matrix whose entries are numbers between 0 and 255, with 0 corresponding, say, to black, and 255 to white. The brain MR images are stored in the database in JPEG format.

3.2 Preprocessing

In preprocessing some basic image enhancement and noise reduction techniques are implemented. Apart from that different ways to detect edges and doing segmentations have also been used. The purpose of these steps is basically to improve the image and the image quality to get more surety and ease in detecting the tumor. The basic steps in preprocessing are the following:-Image is converted to gray scale image in first step. Noise is removed if any the obtained image is then passed through a high pass filter to detect edges. Then the obtained image is added to original image to enhance it.

3.3 Implementation of TFR Algorithm

The general scheme of the proposed Texture Fragmentation and Reconstruction (TFR) segmentation algorithm which follows the splitting-and-merging paradigm is shown in Fig.3.1.

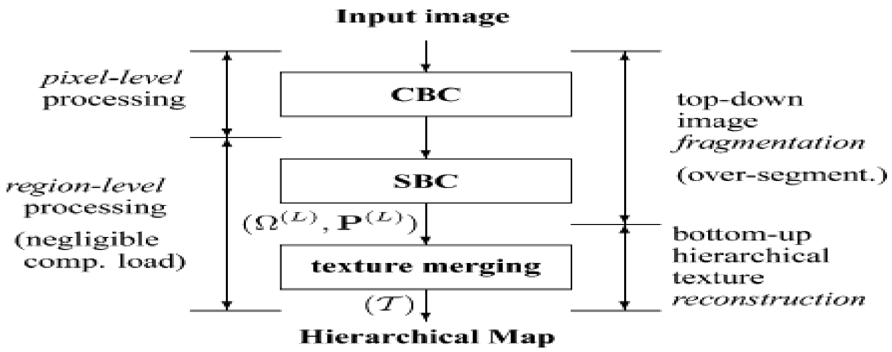

Fig 3.1 TFR flow chart

The image to be segmented is then a composition of an unknown number of different textures whose corresponding models are unknown as well and need to be estimated during the process of texture identification. The model fitting consists in estimating the states at the finest scale and the hierarchical tree which univocally defines each intermediate state.

The determination of the number of textures of a given image, classically referred to as cluster validation problem, is strictly related to the spatial scale (hence to the hierarchical structure) at which we are interpreting the image. When the scale is not fixed somehow, the cluster validation becomes an ill-posed problem.

The proposed solution is quite simple. The first two blocks, CBC (color based clustering) and SBC (spatial based clustering), perform an over-partition of the image that provides the initial finest-scale texture states $\Omega^{(L)}$which are, therefore, progressively related in the last merging process yielding the desired hierarchical segmentation with the associated tree structure T.

Texture Fragmentation and Reconstruction (TFR) algorithm, which first extracts a proper number of terminal states through the top down fragmentation step, composed of blocks CBC (Color- Based Clustering) and SBC (Spatial-Based Clustering), and then relates them by means of a recursive bottom-up merging step, as to reconstruct the whole hierarchical structure.

In order to perform such a classification task, the first CBC block outputs a pixel-by-pixel "color" classification in color states, also referred to as partial (MMC) states. At this level each group of adjacent pixels having a same label are assigned to an image "fragment" and all subsequent TFR processing is made considering fragments (rather than pixels) as atomic elements. All contours are, therefore, fixed in the CBC step, and later, in case, they can only disappear because of region merging. Each color state is, therefore, further split in (full-defined) states by the SBC block) which operates a clustering aimed at putting together fragments with similar MMC features. The main advantages of the proposed technique can be summarized as follows.

• **Robust**. Due to its region-based formulation and contrary to pixel-based models, the one proposed here is able to represent spatial interactions at multiple scales, leading to a nested hierarchical segmentation. Therefore, it does not require the choice of a specific observation scale, whose selection is left to the user, and the resulting algorithm is quite robust.

• **Fast**. Another consequence of modeling the image at a region level is the strong reduction of computational load, since the image processing involves regions, instead of pixels.

• **Blind**. The algorithm can be considered unsupervised because it does not require prior learning of involved textures, in spite of few non critical tuning parameters.

Texture Fragmentation and Reconstruction (TFR) segmentation algorithm is based on Hierarchical Multiple Markov Chain Model.

Hierarchical Multiple Markov Chain Model

It can be used for the task of hierarchical segmentation. We have also shown that such a model is completely defined by the triple $(\Omega^{(L)}, \mathbf{P}^{(L)}, T)$, and motivated the restriction on T to be a binary tree.

The proposed modeling provides region-wise features which carry information about region shape and contextual region interaction. The starting point for the construction of the image model is an appropriate image partition in which each segment corresponds to an "elementary texture," or simply "elementary state," that will be a collection of connected regions which are close both in their color response and in their contextual model features which account for region shape and interactions among neighboring regions. A complete hierarchical description of the image is then obtained by pair wise associating and merging together the so defined elementary states, implicitly providing a set of progressively coarser resolution textures, from the initial partition to the final single full-image state.

The determination of the number of textures of a given image, classically referred to as the cluster validation problem, is strictly related to that of finding the internal structure of each single texture. Indeed, according to the H-MMC modeling, a texture is nothing but a local visual property of a surface where the locality has to be meant at multiple spatial scales. This definition allows describing complex textures but it also says that textures which seems distinct at fine spatial scale collapse in a single texture, sooner or later, at a coarser scale, even if their spatial interaction is weak.

The obtained Hierarchical MMC (H-MMC) stack can be formally defined as follows. Let $\Omega^{(L)}$ be the state set at a given "scale", the transition probability matrix for any chain (direction) j=1….8 (describing both intra- and interstate transitions) is defined as

$$P_j^{(n)} = \{ p_j^{(n)}(\omega'/\omega':\omega',\omega\ \varepsilon\Omega^{(n)}) \qquad [3.1]$$

The H-MMC model is consequently associated with the transition probability set

$$P=\{ P_j^{(n)} : 1\leq j \leq 8,\ 1\leq L \leq n\} \qquad [3.2]$$

and $P^{(n)} =\{ P_j^{(n)} : 1\leq j \leq 8 \}$ is just the nth MMC model component. According to the H-MMC modeling we must somehow relate progressively the elementary textures until we have a unique state representing the whole image.

3.3.1 Color-Based Clustering (CBC)

The color segmentation task (CBC) is here achieved by means of the tree-structured MRF (TS-MRF) model-based algorithm. In the proposed system we have used two classes. One for tumor tissues color and another one is non tumor tissues. In such a model, named tree-structured Markov random field (TS-MRF), the whole image is associated with a tree of regions segments, and each elementary region with a leaf in such a tree, which is progressively singled out by means of a sequence of binary decisions.

This algorithm has several characteristics which are attractive in this context. It uses a MRF prior modeling which helps to regularize elementary regions, improving the robustness with respect to the noise. Moreover, a data likelihood description based on a multivariate Gaussian modeling helps to take into account the correlation in the color space. Finally, its tree structured formulation speeds up the processing, ensures convergence to the desired number of classes, and reduces large-scale effects thanks to its progressive localization. Tree-structured classification exhibits a number of additional advantages with respect to one-shot or "flat" classification let us briefly summarize the most important.

Speed. A binary segmentation is much simpler than K-ary segmentation. Moreover, in a tree-structured segmentation process, the image size keeps decreasing while descending the classification tree.

Adaptivity. Flat MRFs are usually homogeneous, meaning that their parameters do not adapt to local statistics of the image.

Interpretability. As stated above, segmentation is often only the first step of more complex processes, such as classification, compression, image understanding. A flat segmentation provides little or no insight about the algorithm functioning, and even less space for interacting with it; on the contrary, tree-structured segmentation amounts to a sequence of binary decisions that are easily tracked, interpreted, and even guided by the end user if needed. It is worth pointing out that this tree-structured MRF is completely different from the multi-resolution tree-based models, where each node bears a label from the common state space {1…..K}.

3.3.2 Spatial-Based Clustering (SBC)

The color segmentation provided by CBC is passed to the spatial-based clustering (SBC module) which further splits each of the color states in order to generate the state set $\Omega^{(L)}$, where each $\omega \in \Omega^{(L)}$ is associated with a cluster of fragments which are, therefore, similar (the color has been already taken into account) also with respect to the contextual information carried by the MMC features. A large, compact class, with no dominant neighbor, and, hence, a large TS, is probably a complete texture that should be considered for merging only in the last steps of the process. The color of a region only partially defines its state2, the SBC applies to each set of elements with common color, as to split it in subgroups which are homogeneous, that is providing the desired states. Based on fragment-wise features, each color state is, therefore, split by clustering its fragments by means of a simple K-means algorithm. Notice also that the product of the first two terms is an indicator of the spatial scale of the class, while the third one measures the interaction between the class and its dominant neighbor.

In principle, a joint estimation of $\Omega^{(n)}$ and $P^{(n)}$ should be provided, for example by means of some iterative procedure which starts from an initial state set and alternates the computation of $\Omega^{(n)}$ and $P^{(n)}$ until convergence. We have tested this solution, but the results were not satisfying because of two main reasons: a) the curse of dimensionality into the feature space since is definitively too large b) the instability of the iterative process.

Transition probability matrices and scores are then computed for the merged classes and their neighbors (a task of negligible complexity, since it is carried out at the class-level with no pixel wise computation) and the process go on recursively until a single node is reached. Once the complete sequence of merging is defined, a nested hierarchical segmentation is obtained. Therefore, the user can select the segmentation that better serves his/her current needs. To this end a simple rule for selecting the pruning was suggested which refers directly to the spatial scale of the classes by defining a suitable threshold for the texture score.

3.3.3 Region Merging: The Texture Score

Region merging, or state merging, is nothing but a sequential binary combination of the states driven by a specific parameter, namely the region gain which accounts for the mutual spatial relationships among the corresponding regions. Indeed the merging selection process is not symmetric, as the gain is a measure of the scale of the region weighted by an additional term which quantifies the attraction operated by the other regions candidates for the merging). The scale factor allows to privilege always the merging of small regions so that the final hierarchy is such that micro-textural features are represented at the bottom, while the macro will appear at upper levels, and finally inter-texture merging will be placed at the top of the structure, in order to keep separate the marginal sub-models corresponding to the different textures.

The result of the sequence of steps described above (CBC and SBC) is a partition of the image in regions corresponding to the finest-scale textures, collected as $\Omega^{(L)}$. According to the H-MMC model formulated above, these terminal states have now to be related until all collapse in the macro state associated with the hierarchy root, i.e., with the whole image (coarsest scale), which corresponds to a recursive region merging. The aim of this process is to collect together finer textures in order to get larger and larger (in scale) textures and provide a nested hierarchical texture segmentation.

Since the merging process goes always on until all nodes collapse in the tree root, what we need is a tool that indicates, at each step, which couple of nodes must be merged, that is to say, which classes are most likely to belong to the same texture. In doing this, we should encourage the merging of strongly interacting classes, as they are likely to belong to the same textured area, and take into account short-range interactions before long-range ones. Suppose we have currently four states, u, v, y, w, two of which should be selected for merging. We observe that (corresponding to the black regions) is the current smallest scale texture (this makes a good candidate), and is "spatially" strongly interacting with v. Based on these considerations for each terminal class we define a synthetic parameter called "Texture Score".

$$\mathrm{TS}^{\omega} = \frac{p(\omega)}{\max_{\omega' \neq \omega} p(\omega' | \omega)} \qquad [3.3]$$

and for each step , n= L,L-1,…2,the state with smallest score and its “dominant neighbor” are merged, so as to move from $\Omega^{(n)}$ to $\Omega^{(n-1)}$.

At each step of the merging process, the class with the smallest score is merged with its dominant neighbour w^*, singled out as,

$$\omega^* = \arg\max_{\omega \neq \widehat{\omega}} p(\omega | \widehat{\omega}). \qquad [3.4]$$

IV. EXPERIMENTAL RESULTS

In order to provide a more solid assessment for the proposed technique, this section discusses segmentation results obtained. The figures show the various stages obtained as a result of applying Hierarchical Multiple Markov Chain Model and TFR Segmentation Algorithm.

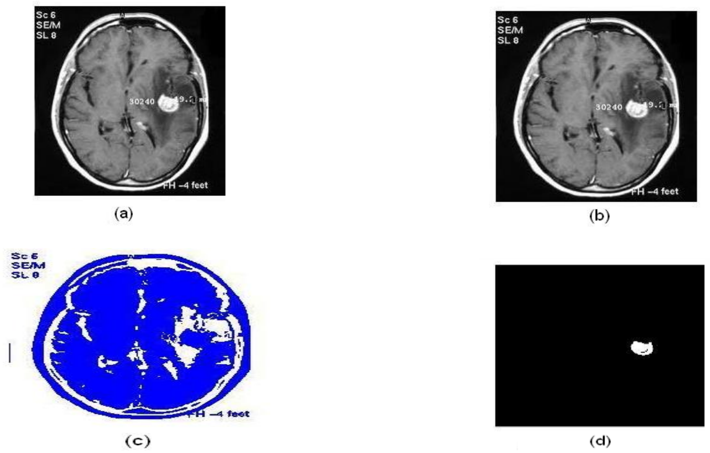

Fig 4.1 a, b, c, d (a) Input Image (b) Preprocessing Image (c) Color Based Clustering (d) Segmented Image.

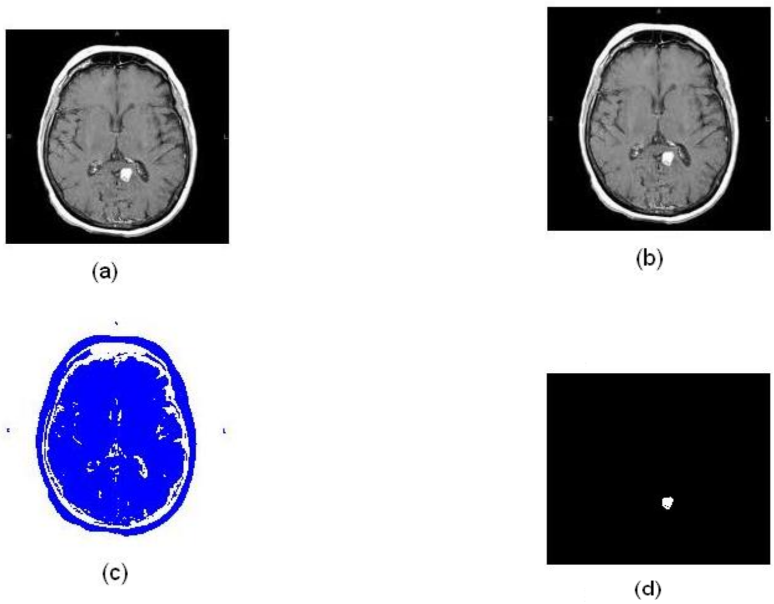

Fig 4.2 a, b, c, d (a) Input Image (b) Preprocessing Image (c) Color Based Clustering (d) Segmented Image.

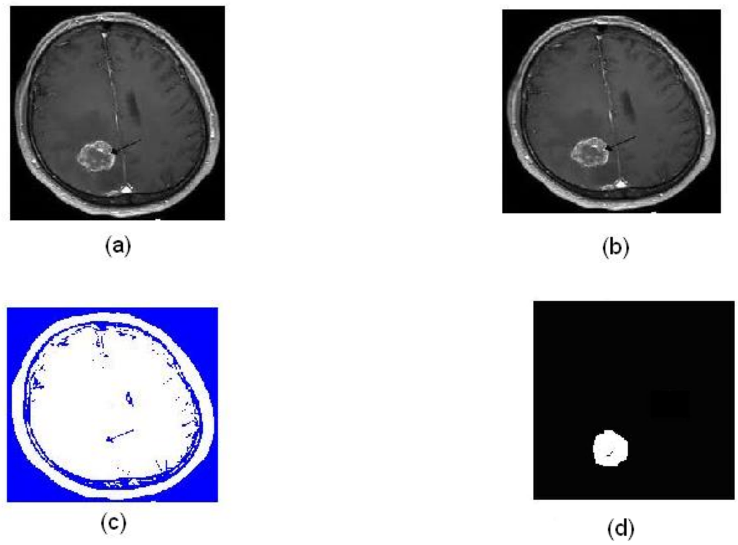

Fig 4.3 a, b, c, d (a) Input Image (b) Preprocessing Image (c) Color Based Clustering (d) Segmented Image.

In figure (a) Input Image (b) Preprocessing Image (c) Color Based Clustering (d) Segmented Image. Fig (a) is the original MRI image from which the tumor is to be differentiated. The first step is Pre-processing, shown in Fig (b), where unwanted noises are removed from the image. The goal of this step is to increase the accuracy and interoperability of the digital data during the image processing phase. To this preprocessed image, Color Based Clustering technique that adapts the tree-structured MRF (TS-MRF) model-based algorithm is applied to obtain the image shown in Fig (c). Finally, to the resulting image, spatial based clustering is applied which results in the segmented image as shown in Fig (d).

V. CONCLUSION AND FUTURE WORK

In this paper we have presented a hierarchical model (H-MMC) for texture representation, particularly suited for unsupervised segmentation, and a related algorithm (TFR). In order to apply the model, the first step of the algorithm is a color-based segmentation, realized by TS-MRF, which provides a rough discrete approximation of the original data to be fitted with the texture model at the region level. The fitting is performed in two steps; the first (SBC) singles out the individual states of the model, the second relates them hierarchically according to the scale of the corresponding regions and their mutual spatial interaction. The bottom-up growth of the structure is controlled by a texture score parameter. TFR outperforms all reference algorithms, mostly because of its ability to capture spatial correlations at multiple scales. The main advantage of the proposed technique is that the system is robust, fast and blind. TFR algorithm has provided encouraging results in several different applications; a few drawbacks need to be mentioned as well, mainly due to some of the simplifying assumptions both in the modeling and the optimization part. Discrimination of micro-textural features is often incorrect, since the small size of component regions makes their region-wise characterization unreliable. A possible solution is to identify small micro-textured regions at the CBC level, or even introduce a new layer with this specific aim. As for spatial clustering, the presence of fragments whose characterization is loose can lead to the definition of unreliable states that incorrectly include many “outliers” whose presence can significantly alter adjacency statistics based on neighboring states. The automatic detection and processing of such critical elements is certainly another point of our future research. Finally, another peculiar problem of TFR is the processing of “continuous” connected regions, which typically occurs for textures containing background constant-colors. In this case, when two neighboring textures have a common color state which presents such continuous elements, due to their large scale they serve mostly as collectors during the region merging, attracting regions from the two different textures and eventually making their separation impossible. In order to overcome this last problem we are currently investigating the possibility of fragmenting continuous regions. Some of the applications of future scope of this project are locate objects in satellite images, remote sensing, biometric security on mobile device and industrial automation.

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