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Feature-based approach toward computer aided detection and diagnosis

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Abstract

We present a framework for computer aided detection and diagnosis based on segmented tissue mixtures in each voxel of the image. Detection is based on both the geometry and texture. Diagnosis is based on both the texture and feature extracted from the mixture segmentation.

Keywords: Mixture segmentation; Feature extraction; Feature-based visualization

1. Introduction

With advance of medical imaging technologies (including instrumentation, computer and algorithm), the acquired data information is getting so rich toward beyond the human's capability of visual recognition and efficient use for clinical assessment. The concept of computer or ideal interpreter has been around for many years. Computer technologies can make somewhat simple abnormality detection and disease diagnosis from the images, but could not replace the human ability to analyze complex information. On the other hand, computer technologies can "see" some details inside the images, while human might not be able to see. A computer interpreter can efficiently and consistently "read" many images, while human might make inconsistent assessments in an inefficient manner. Therefore, computer aided detection (CAD) and computer aided diagnosis (CADx) become more desirable and are now under development by many research groups in the world. The former one aims to detect any abnormality from the images, while the later one intends to differentiate the detected abnormality as either benign or malignance or to identify the detected abnormality as a most possible disease.

We view image-based CAD and/or CADx more generally as a computer-aided procedure to assist physicians for medical diagnosis, treatment/surgical planning, and follow-up evaluation of disease management. This process is thought as an information processing.

Images acquired from a patent carry all the subjective and objective information. This information itself may or may not be enough to make a decision. For this reason, physicians' input as additional information would be useful to the decision-making. However, in more cases, presentation of the patient image information to the physician for clinical assessment is limited by currently available technologies and, therefore, results in many undetermined cases. With advent of advanced computer technologies and sophisticated image processing algorithms, those detailed information beyond human visual ability to acquire from the images can be extracted and displayed in real time for physician's assessment. With both physician's input of additional information and computerized extraction of more details from the images, it is expected to decrease dramatically the number of undetermined cases. In this paper, we present a unique CAD/CADx system, which addresses both the information processing and information visualization issues for medical diagnosis, treatment/surgical planning, and follow up evaluation. The information processing is detailed by the following two sections of (i) mixture-based image segmentation and (ii) featture analysis of the mixture segmentation with the options of physician's editing. The editing integrates physician's experience into the clinical assessment. The information visualization is detailed in the third section of feature-based volumetric/surface rendering.

2. Mixture-based Image Segmentation

Given an acquired image or a series of images with finite voxel size (voxel is an image element in three dimensions and is called as pixel in two dimensions), conventional segmentation algorithms label each voxel as a single class or tissue type or object [2, 5, 10]. This kind image classification limits quantitative accuracy on the contents inside the voxels and on the spatial location of tissue boundaries. Our segmentation method not only labels each voxel as the conventional algorithms do, but also quantifies the contents as percentages of tissues inside that voxel [3, 4, 6]. (The percentage vector of tissues inside a voxel is called as mixel). This later kind image segmentation has unlimited spatial resolution on the tissue boundaries and achieves the most accurate measurement on the voxel contents. Furthermore, the neighborhood system of mixture segmentation can provide tissue growth tendency, in addition to the anatomical structure of the tissues. Presentation of both the anatomical structure and growth tendency of a tissue type with accurate quantification of the tissue contents shall improve the clinical assessment for diagnosis, treatment/surgical planning, and follow-up evaluation. Our CAD/CADx system is based on the mixture segmentation.

3. Mixture-based Feature Analysis

3.1 Feature Extraction from Mixture Segmentation

User Edited Texture Extraction: Given the mixture segmentation or mixel volume data, we extract a tissue structure based on the similarity of mixels. First, a seed point or voxel is selected by the user for a specific tissue type or object. The percentage of this specific tissue must be greater than other tissue types inside that voxel. The percentage proportion of all tissue types in the mixel provides a characteristic vector reflecting the specific tissue type. All mixels with similar percentage proportions will be grouped together by utilizing region-growing strategies with modification by adding neighbor mixels into consideration. Those mixels with noticeable variation by vector similarity threshold measure will be labeled as layer mixels. Any unexpected small variation in the fully automated segmentation will be corrected at this stage by the physician.

Volumetric Analysis: For volumetric quantification on different tissues, the layer mixels provide a blurred boundary to separate two tissues. The volumetric measures of these two tissues will include the blurred boundary and count their percentages respectively. Volumetric analysis has a wide application in neural disorder diagnosis. One example is the diagnosis of multiple sclerosis (MS) and evaluation of a treatment means by measuring the brain atrophy [1, 3]. If we do not provide any treatment during a time course, the volumetric variation or atrophy measure itself will be an effective means for the MS diagnosis. Differentiation of benign or malignance of a detected pulmonary module by the volumetric measures in a time period is another example for diagnosis of a specific disease by volumetric analysis. The unique aspect of our CAD/CADx system is its accuracy due to the mixture segmentation.

Treatment/Surgical Planning: For surgical planning, the layer mixels will be colored as differently from the two or more tissues invading the layer. The portion of the layer with lesion percentage will be operated [7]. The mixer layer provides the most accurate reference to the surgeon to operate on the target.

Surface Geometric Analysis: Based on the mixture segmentation, a tissue/object boundary can be extracted from the mixel layer with high accuracy. By utilizing the neighboring mixels, the tendency of the surface movement can be quantified. The accurate surface geometry provides a means for CAD on abnormality; and the tendency of the surface movement, combining the texture of the mixel layer, provides a means for CADx on the detected abnormality.

For visualization purpose, we shall identify some area with high suspicious for physicians' inspection. Presenting accurately the features on these suspected areas is another key point of our CAD/CADx system. As we pointed out before, we will provide not only the tissue structure, but also the tissue growth tendency by analyzing the features of the mixture segmentation. In the followings, we present our CAD/CADx system for visualization-based clinical applications.

3.2 Principal Direction Feature of Mixture Segmentation

One feature in the segmented mixture data volume is the principal direction. Principal direction is an important attribute to describe the tissue/object surface. In our method, we modify the definition of the principal direction to fit the segmented mixel volume. For object/tissue l in a given mixel $M_{i,j,k}$ (or voxel with mixture tissues inside), there exists a percentage $P^l_{i,j,k}$ of object l inside the mixel, provided by the segmentation. Thus, there exists an iso-surface in the mixture volume across all mixels $M^l_{k,s,t}$ with percentage $P^l_{k,s,t} = P^l_{i,j,k}$. The principal direction of tissue l at $M_{i,j,k}$ is defined as the principal direction of this iso-surface. To calculate the principal direction of each mixel, we have developed a neighbor matrix method to extract the principal direction from the mixture volume rapidly. Firstly, we use the discrete difference method to obtain the normal vector of object/tissue l in mixel $M_{i,j,k}$

$$N^l_{i,j,k} = (P^l_{i+1,j,k} - P^l_{i-1,j,k} , P^l_{i,j+1,k} - P^l_{i,j-1,k} , P^l_{i,j,k+1} - P^l_{i,j,k-1}). \tag{1}$$

Secondly, for each object l in mixel $M_{i,j,k}$, we create a 3D neighbor array A. Thus A can be represented as

$$\{ A_{k.s.t} \,|\, A_{r.s.t} = (P^l_{r,s,t}, N^l_{r,s,t}) \} \;\; r \in [i\text{-}1, i+1],\, s \in [j\text{-}1, j+1],\, t \in [k\text{-}1, k+1]. \tag{2}$$

According to the similarity between the percentages of the neighboring mixels, we assign a value to each element/voxel in the neighbor array A. Collecting all value in the array, an index is constructed. Using this index, we can search, in a check-list, for several candidate directions, along one of which the maximum curvature will occur. Using the position and the normal information of Eqns.(1) and (2), we can figure out the principal direction among these candidate directions. This method only uses the neighboring mixel information to calculate the principle direction. It needs a little calculation effort. Furthermore, the neighbor arrays A of two adjacent mixels are similar, so we can use this fact to speed up the algorithm. Collecting all the principal direction information, a feature based vector volume is then constructed.

4. Feature-based Volume Rendering

Our presented rendering algorithm is composed of three sections: (1) converting feature vector volume to stroke based scale volume; (2) constructing the mixture scale color volume; and (3) rendering the final mixture scale color volume. The flow chart is shown by Figure 1 below.

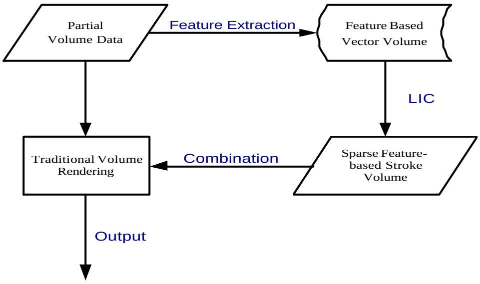


Figure 1. The flowchart of our feature-based rendering algorithm.

4.1 Converting Feature Vector Volume to Stroke Scale Volume

For the feature vector volume, we need to convert the feature vector volume to stroke volume. In the latter volume, all vector are classified and quantatized. The continuous vector volume is rendered as a 3D texture volume -- stroke based scale volume. To accomplish this objective, we utilize two methods: (i) modified line integral convolution (LIC) method and (ii) streamline method.

Modified Line Integral Convolution (LIC) Method: The LIC method is a popular method to display the vector volume by the texture analysis. This method utilizes the vector field *V* and the input texture data *Tex* to create another texture data *Output*, whose pattern can describe the vector field clearly. The crucial conversion function is

$$output_{i,j,k} = \int_{s_{i,j,k}-L}^{s_{i,j,k}+L} k(s - s_{i,j,k}) Tex(s\ (s))ds\,. \qquad (3)$$

In the original method, the input texture data volume *Tex* is a continuous white noise texture volume. We utilize a sparse cluster texture as the input texture *Tex*. The texture volume is composed of a given number of clusters. Using this texture, the output texture volume will be a sparse stroke volume. The strokes can describe the vector field very well. The distribution of the clusters is controllable. This means that by adjusting the corresponding variable, we can control the distribution and the position of the strokes.

Streamline Method: Streamline method is another method to describe the vector field. At first, we select several seed points in the vector volume. These seed points can move along a curve whose gradient at a given position is equal to the vector value at that location. By recording the moving track of the seed point, a sparse stroke volume, which is composed of the track voxels, is created. Same as the modified LIC method, the distribution of the seed points can be controlled by the feature and mixel information. Thus the surface information is converted into the volume information. By controlling the distribution of the seed points and the other attributes of the LIC algorithm, different stroke volumes can be generated in which different interesting feature sections are focused at different "directions".

These two methods have their own advantages. The modified/advanced LIC method can describe the details of the vector volume, and its implementation is simple. The streamline method can save a great calculation cost, so it is more suitable for the non-dense vector volume. If the distribution of the strokes is dense and the vector field is continuous, we prefer to utilize the LIC algorithm. If the distribution of the strokes is sparse, we may use the streamline method.

4.2 Constructing Mixture Scale Volume

The sparse stroke based volume is a scale color volume has the same dimension as the original mixture volume. We integrate the stroke based volume *S* with the original mixture volume *O* into a final mixture volume *M*

$$M^{l}_{i,j,k} = S^{l}_{i,j,k} \oplus O^{l}_{i,j,k} \qquad i,j,k \in [1,n], \quad l \in [1,t] \tag{4}$$

where *n* is the dimension of the data volume, *t* is the number of tissues in a mixel, and $\oplus$ is the interpolation operator.

The information of two volumes includes color, opaque and so on. The interpolation operator can be overlay, addition, minus, line interpolation, and so on. Using the interpolation operator, the strokes, which describe the feature in the volume, can be embedded into the original volume. Thus all information can be synthesized into a scale volume. Using different operator, we can get different effect.

4.3 Rendering the Integrated Volume by Volume Rendering

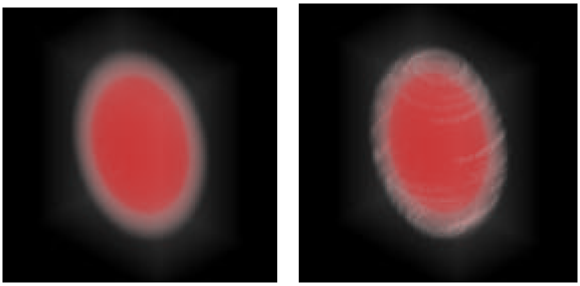
For the final integrated volume, we use volume-rendering algorithm to render the final projected image. Volume rendering is a popular and efficient method to render the scale volume. Before volume rendering, we construct a non-mixture scale color volume *C*

$$C_{i,j,k} = \sum_{l=1}^{t} f(M^{l}_{i,j,k}) \cdot p^{l}_{i,j,k} \tag{5}$$

where $p^{l}_{i,j,k}$ is the percentage of tissue/object *l* in mixel (*i,j,k*), and *f* is the illumination function.

After computed the color volume and assigned each voxel the corresponding opaque, a conventional volume rendering can calculate the color of each voxel on the projected image. Because a conventional volume rendering needs much calculation time, instead we used the latest 3D texture-based and hardware assisted volume rendering [8]. The rendering time was noticeably shortened. We also developed a new image based volume rendering algorithm -- sphere light field algorithm to further improve the speed of volume rendering [9]. By constructing a sphere light field, this algorithm can achieve the real time rendering of the volume data.

An example of demonstrating our feature-based visualization is illustrated using a 3D elliptical sphere volume image, as shown by Figure 2 below. There are two objects or tissues in the volume dataset: the inner one is object 1 (red); and the outer one is object 2 of white color. All the partial/mixture volume image and stroke volume are rendered by a traditional volume rendering method. As shown in Figure 2(a), the rendered original image without the stroke volume shows only an outline of the two objects with some degree of blurring. The rendering of the combination of the partial/mixture volume image and the stroke volume shows clearly the features of tissue/object growth tendency as seen in Figure 2(b), i.e., after invoking the strokes into the rendering of the partial/mixture volume image.



(a) (b)

Figure 2. (a) The original 3D partial volume image. (b) The rendering result with feature extracted from the partial volume image data.

References

1 Christodoulou, C., Krupp, L., Huang, W., Chen, D., Melville, P., Scherl, W., Perone, P., Morgan, T., Liang, Z., Roche, P., Peyster, R., and Roque, C. (2001), "Cognitive correlates of quantitative MRI and MRS in MS," *Neurology*, **56**: A191-192.

2 Clark L., Velthuizen R., *et al.* (1995), "MRI segmentation: methods and applications," *J of MRI*, **13**: 343-368.

3 Li, L., Li, X., Huang, W., Christodoulou, C., Chen, D., *et al.* (2002), "A novel mixture-based segmentation algorithm for quantitative analysis of MS using multi-spectral MR images," *10th Intl Soc MR in Medicine*, to appear.

4 Liang, Z., Jaszczak, R., & Coleman, R. (1992), "Parameter estimation of finite mixtures using the EM algorithm and information criteria with application to medical image processing," *IEEE Trans Nucl Science*, **39**: 1126-1133.

5 Liang, Z. (1993), "Tissue classification and segmentation of MR images: research on statistical approaches offers avenue toward automation," *IEEE Engin. in Medicine and Biology*, pp. 81-85.

6 Liang, Z., MacFall, J., & Harrington, D. (1994), "Parameter estimation and tissue segmentation from multispectral MR images," *IEEE Trans on Medical Imaging*, **13**: 441-449.

7 Smouha, E., Chen, D., Li, B., and Liang, Z. (2001), "Computer-aided virtual surgery for congenital aural atresia," *Otology and Neurotology*, **22**: 178-182.

8 Wang, Z. and Liang, Z. (2002), "Feature based rendering for 2D/3D partial volume segmentation datasets," *SPIE Medical Imaging*, to appear.

9 Wang, Z. and Liang, Z. (2002), "Sphere Light Field Rendering," *SPIE Medical Imaging*, to appear.

10 Young & Fu (1986), *Handbook of Pattern Recognition and Image Processing*, New York: Academic Press.