INTERACTIVE GRAPHICAL SYSTEM FOR SEGMENTATION OF MULTIMODAL MEDICAL VOLUMES USING FUZZY CLUSTERING

P. Boguś(2), A.M. Massone(1), F. Masulli(1,3) and A. Schenone(4)

(1) Istituto Nazionale per la Fisica della Materia, Via Dodecaneso 33, 16146 Genova, Italy
(2) Medical University of Gdańsk, Department of Physics and Biophysics, ul. Dębinki 1 80-211 Gdańsk, Poland
(3) DISI - Dipartimento di Informatica e Scienze dell'Informazione Università di Genova, Via Dodecaneso 35, 16146 Genova, Italy
(4) Istituto Nazionale Ricerca sul Cancro Largo R. Benzi 10 16132 Genova, Italy
Emails : gogo@amedec.amg.gda.pl, {masulli,massone}@ge.infm.it, schenone@cisi.unige.it

Abstract.
The paper presents a computerized interactive graphical system for multimodal medical volumes segmentation. We present a new generation of the system obtaining by applying fuzzy methods in clustering. We give an outline of fuzzy c-means algorithm and we report the results obtained by using it to multimodal medical volumes segmentation.

Key words: multimodal medical volumes, fuzzy clustering, segmentation, medical application.

1. Introduction

The visual inspection of medical volumes obtained by new imaging techniques (such as CT, MRI, PET or SPECT [13]) for therapy monitoring or other applications such as medical diagnosis or surgery planning is a very complex and time expensive task. Moreover the increasing availability of imaging techniques (see e.g. SPECT or PET) gives the perspective of a near future when a physician will have to manage huge amount of volumes acquired with different imaging methodologies (multimodal imaging volumes).

Many medical tasks such as diagnosis, therapy monitoring or surgery planning can receive a big support by imaging techniques, but the visual inspection of a big set of images helps physician to exploit the available information only partially. In order to extract the salient information embedded in multimodal medical volumes a number of analysis methods have been presented in the literature [3, 4, 5, 8, 9, 10, 12, 18, 19, 20, 21].

The main goal is to give to the physician, in the place of many separate volumes, one segmented volume containing complementary information from multimodal volumes.

In the past the segmentation was usually done by edge detection techniques [3] but this techniques are not very useful in medical applications due to the noise embedded in the medical images.

More effective techniques can be attained both by supervised and unsupervised methods. Supervised methods have been largely employed in medical imaging segmentation studies but they require conditions hardly satisfied in the clinical environment because labeling is an expensive task (especially for huge volumes) and relevant biases may be introduced by physician unskilled or fatigued. On the contrary, unsupervised approaches appeared quite innovate and interesting [10]. What is worth to underline an unsupervised approach self-organize the implicit structure of data and make blind segmentation that, in principle, can be possibly refined in following interactive steps by the physician [3, 7].

In this paper we present the recent development of a computerized graphical system supporting the full segmentation procedures of multimodal medical volumes that has been developed by our group for many years [18]. The core of our system is a segmentation of multimodal volumes by unsupervised clustering. We must point out that voxel values, especially at the border between volumes of interest, correspond to mixtures of different anatomical tissues, because of the low resolution of sensors. As a consequence, borders between tissues are not strictly defined and memberships in boundary regions are intrinsically fuzzy. Hence we included in our system some fuzzy clustering algorithms. The fuzzy methods are acting as filters which reduce an effect of sampling for the neighboring voxels.

Additionally, the fuzzy methods appear to perform an efficient unsupervised clustering adaptively and usually they are not affected by the dimensionality of the feature space. Sometimes, adding some kind of smoothness to the voxel classification would be very helpful in order to better define surfaces of the anatomical objects described by segmentation. This may be accomplished by fuzzy clustering methods which are robust in their nature and are able to produce a voxel classification related to the membership function of clusters.

Hence together with a description of the computerized interactive graphical system (see Section 2) we will present in this article the background of clustering fuzzy methods (see Section 3) and some results of applying the fuzzy c-means algorithm [2] to the multimodal medical volumes (see Section 4).

2. Graphical interactive system for multimodal medical volumes segmentation.

The system we are developing is mainly addressed to the interactive segmentation of multimodal medical volumes by physicians in order to exploit in depth the information hidden in clinical images.

The core of the system lays in segmentation techniques through clustering and a strongly interactive Motif/Open-GL graphical environment. The main direction is going from multimodal MRI volumes to classification.

The graphical system for multimodal medical volumes segmentation has been developed as a fully modular system whose parts acting independently from each other. It contains five main modules (functions) so the following steps may be used in the analysis sequence:

1. Visualization of data set.
2. Reduction of dimensionality.
3. Unsupervised clustering.
4. Voxels classification.
5. Interactive post-processing.

For classical MRI images the three-dimensional feature space is usually simply given from three complementary T1 (*spin lattice relaxation*), T2 (*transverse relaxation*) and PD (*proton density*) weighted volumes. But in general during analysis of medical images, the process of feature extraction can explode in a big number of feature space dimensions. In such a situation the reduction of dimensionality can simplify the complexity of a problem [18].

Additionally, in practice, multimodal volumes should be registered with a fully spatial correlations of voxels in separate volumes. In general, in the preprocessing step, some geometrical transformation such as scaling or centering should be performed on volumes to obtain their full spatial correlation.

Voxels classification in the system is obtained automatically after clustering process in a feature space is completed. To describe this approach let us consider a multimodal volume resulting from the spatial registration of a set of s different imaging volumes. We may notice that its voxels are associated with a vector of s values, each representing the intensity of a single feature in a voxel. In other words, the s different intensity values related to all the voxels in such multimodal volumes can be viewed as the coordinates of the voxels within an s-dimensional feature space where multivariate analysis can be made.

Two different spaces have therefore to be considered for a more complete description of the segmentation problem:

- a 3D image space defined by the spatial coordinates of the data set, and
- a multidimensional feature space, as described before.

The point of segmenting multimodal volumes lays in definition of clusters within the s-dimensional feature space and the classification of all the voxels of the volumes to the resulting classes. The relationship between these two spaces plays a very important role in understanding the data structure.

Many unsupervised clustering algorithms are available in our system from the classical hard c-means (see Duda [1]), through the Capture Effect Neural Network [14, 18] to fuzzy clustering algorithm that will be described in the following section [18, 19, 20, 21].

The last and one of the main steps performed by the system is an interactive post-processing which gives user a possibility to influence resulting images. An interactive module allows to refine clusters both in the feature space and in the image space. User can correct voxels in clusters. This way clusters can be suppressed and merged or even modified by adding or removing voxels.

What is worth noting that the system gives a possibility to show any transversal, coronal, and sagittal view of the eventually segmented volume. Actually, one can move through the volume to visualize orthogonal planes in all directions.

3. Fuzzy c-means algorithm of clustering

In the classical clustering problem we have a set

$$\Omega = \{\vec{x}_i; i = 1, ..., n\} \tag{1}$$

of n data vectors (a training set) and a set of c clusters. In general one introduces the probabilities

$$p_{ij} = p(\vec{x}_i \in cluster_j), \tag{2}$$

that the data point $\vec{x}_i$ belongs to the cluster j. In the fuzzy literature, this association probability p_{ij} is also called the fuzzy membership in clusters. For each i we have the normalization condition

$$\sum_{j=1}^{c} p_{ij} = 1. \tag{3}$$

We usually introduce the local energy (cost function)

$$E_{ij} = E(\vec{x}_i \in cluster_j) \tag{4}$$

of association of the data point $\vec{x}_i$ to the cluster j and then the total averaged energy is

$$< E > = \sum_{i=1}^{n} \sum_{j=1}^{c} p_{ij} E_{ij}. \tag{5}$$

A fuzzy approach based on using fuzzy set methods (see e.g. [6, 15]) and their application to pattern recognition was proposed by Bezdek (see e.g. [2, 10]). One can find many examples of fuzzy approach to clustering [11, 17, 19, 21].

The fuzzy methods appear to be capable to perform adaptively an efficient unsupervised clustering and they are not affected by the dimensionality of the feature space. Moreover they are able to produce a voxel classification related to the membership function of clusters what can better define surfaces of the anatomical objects described by segmentation.

The fuzzy c-means algorithm of clustering proposed by Bezdek [2, 10] is based on the concept of so-called fuzzy partition of the data set.

Assume that we have the data set $\Omega = \{\vec{x}_i; i = 1, ..., n\}$ where each data vector $\vec{x}_i \in \mathbf{R}^p$. Assume also, there is a fixed number of clusters c with a set of centroids

$$Y = \{\vec{y}_j; j = 1, ..., c\}$$

where each vector $\vec{y}_j \in \mathbf{R}^p$.

Let V_{nc} denotes a set of n $\times$ c matrices with real values. The fuzzy c-partition of the data set Ω is any matrix v $\in V_{nc}$ with the following properties:

- $\forall_{ij} \quad v_{ij} \in [0, 1]$,
- $\forall_i \quad \sum_{j=1}^{c} v_{ij} = 1$,
- $\forall_j \quad 0 < \sum_{i=1}^{n} v_{ij} < n$.

This is a matrix where each row represents the membership rates of the given vector to the clusters and each column represents membership function for the given cluster for all vectors.

The set of all matrices v $\in V_{cn}$ which satisfy the above conditions will be denoted as M_{fc}. Next we define the objective function (called fuzzy c-means functional) as:

$$J_m = M_{fc} \times \mathbf{R}^{cp} \to \mathbf{R}^+$$

$$J_m(v, Y) = \sum_{i=1}^{n} \sum_{j=1}^{c} (v_{ij})^m (d_{ij})^2, \tag{6}$$

where

- m is a weighting exponent, m $\in [1, \infty)$,
- d_{ij} is a distance of a given vector $\vec{x}_i$ to the centroid $\vec{y}_j$ of cluster j (also called the energy, cost function or similarity measure),
- v $\in M_{fc}$ is the fuzzy c-partition of the data set Ω and
- $Y = \{\vec{y}_1, ..., \vec{y}_c\} \in \mathbf{R}_{cp}$ is a set of cluster centroids.

On the basis of the work by Bezdek [2] the fuzzy c-means algorithm can be described as follows:

1. Let us define two sets:
   - The set I_i
     $$I_i = \{j; \ \ 1 \le j \le c \ \text{ and } \ d_{ij} = 0\}.$$
     For the given $\vec{x}_i$ the set I_i is a set of those cluster indices for which the vector $\vec{x}_i$ is equal to the center $\vec{y}_j$ of the given cluster, which means $d_{ij} = 0$. The number of elements in the set I_i will be denoted by i_i.
   - The set I'_i
     $$I'_i = \{1, 2, ..., c\} - I_i.$$
     For the given $\vec{x}_i$ the set I'_i is the set of those cluster indexes for which $d_{ij} \neq 0$.
2. We fix c ($2 \le$ c < n) and m (m > 1).
3. We randomly initialize the matrix $v_{ij}^0 \in M_{fc}$.

4. Now in the given step t (where t= 1, 2, ...)
   - we calculate fuzzy cluster centroids by the formula
$$\vec{y}_j^{\,t} = \frac{\sum_{i=1}^{n} (v_{ij}^{t-1})^m \, \vec{x}_i}{\sum_{i=1}^{n} (v_{ij}^{t-1})^m} \tag{7}$$
   for each j = 1,...,c.
   - we calculate a new matrix v_{ij} using calculated earlier values of $\vec{y}_j^{\,t}$, which means that for each i=1,...,n
     - we check if there exists such a value of j that $d_{ij} = 0$ (we are finding the set I_i),
     - if such j exists (what means that $I_i \neq \emptyset$) then
       * for j not belonging to I_i we put $v_{ij} = 0$ and
       * for j belonging to I_i we put $v_{ij} = \frac{1}{i_i}$,
     - when such j does not exist (which means that $I_i = \emptyset$) then for all j
$$v_{ij} = \frac{1}{\sum_{s=1}^{c} \left(\frac{d_{ij}}{d_{is}}\right)^{\frac{2}{m-1}}} \tag{8}$$
     - in effect we find the new matrix v_{ij}^t.
   - we calculate the error as
$$\Delta = \sum_{j=1}^{c} |\vec{y}_j^{\,t+1} - \vec{y}_j^{\,t}|^2 \tag{9}$$
   or using the matrix norm as
$$\Delta = ||v_{ij}^{t+1} - v_{ij}^t|| \tag{10}$$
5. If $\Delta \leq \epsilon$ the calculation stops, in opposite case it continues the calculation increasing t by one and starting from point 4.

Although it is not immediately obvious, the fuzzy c-means algorithm reduces to hard (classic) c-means algorithm when m=1 and the d_{ij} is the Euclidean distance [2].

4. Applications

The system for multimodal medical volumes segmentation has been developed on a Silicon Graphics Indy R4600 workstation in a X11 Unix environment by using standard Motif/Open-GL libraries.

The fuzzy c-means algorithm was applied to the segmentation of white matter, gray matter, cerebrospinal fluid, and the skull, using MRI images of the head. We used three volumetric data sets of dimensions 171x220x143, representing *spin lattice relaxation* (T1), *transverse relaxation* (T2), and *proton density* (PD). The MRI data were taken from a healthy volunteer. In order to test the general performances of the fuzzy clustering algorithm with a large and very noisy data set, no corrections were made to reduce the inter-slice variability of image intensity and no reduction of dimensionality has been performed. Example orthogonal views of three-dimensional volumes taken into consideration are presented in Figure 1.

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Figure 1. Example slices of the T1, T2 and PD volumes (from left to right) in XY, XZ and YZ views.
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The fusion of T1, T2 and PD weighted volumes defines a three-dimensional feature space, in that each triplet of intensity values in the data set is represented by a point in a 3D feature space. Our main task was to detect clusters in such a feature space and to use them for segmenting the input volumes. To achieve this aim we used the fuzzy c-means algorithm of clustering in the three-dimensional feature space. The fuzzy c-means algorithm was initialized with c=5 which results from the anatomical knowledge of the problem. The parameter m was set to 2, as suggested by Pal and Bezdek [16]. On a Silicon Graphics workstation for 3D volumes segmentation the obtained convergence times were about 2-3 minutes.

Additionally in order to speed up the algorithm we tested it using a Reduced Data Base (RDB) by dynamical random sampling. As shown by our results, the random sampling method of the data base reduces the convergence time of the training algorithm maintaining at the same time a high quality of the segmentation of multimodal images. Moreover, the uncorrelation of the data sets used in each training epoch leads to more reliable solutions [20, 19]

The centers of the clusters were initialized at random in the feature space, whereas the stop criterion was:

$$\bigvee_j \quad (\|\vec{y}_j(t+1) - \vec{y}_j(t)\|) \leq \epsilon \qquad j \in [1, c],$$

where t is the iteration index and ϵ is a precision threshold.

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Figure 2. The unsupervised clustering of the feature space in projections into two-dimensional planes T1 versus T2, T1 versus PD and T2 versus PD (top, on the right) and example orthogonal views of segmented image volume in XY, XZ and YZ views (on the left, from top to bottom).
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The resulting clustering of the feature space and example orthogonal views of the corresponding segmented image volume, obtained for original volumes from Figure 1 is presented in Figure 2. One can find there the clustered feature space projected into three two-dimensional planes and example orthogonal views of the segmented volume. There are five clusters in the feature space (labeled using five colors) and one can find corresponding classes (the same color) in the image volume. The segmentation images obtained at the end of the strictly unsupervised classification step are showed without any refinement to point out the notable general performances of the fuzzy clustering algorithm. In fact, these results may be used as an advanced starting point by clinicians. Actually, in a final step, segmentation can be improved, within our system, through a fully interactive interface by introducing the user knowledge in the segmentation process.

5. Discussion and Conclusions

In this article we have presented a computerized, multi-modular, graphical, interactive system which can prepare the segmentation of multimodal medical volumes through an unsupervised approach to clustering. We have described some results on the application of fuzzy methods to MR images unsupervised segmentation.

The presented graphical system, by adding a new quality to medical imaging techniques, appears very useful in medical image analysis. It may be especially useful in oncological treatments to help in delineating volumes to be treated in radiotherapy and surgery, and to quantify the response in terms of tumor mass or detection of metastases. It can support the process of medical treatment, therapy monitoring and surgery planning, especially in oncological surgery where the most important is a precise determination of a tumor place before treatment.

Our system turns out to be very interactive giving the user possibility to display and modify volume data. A friendly graphical interface allows the user to introduce his/her knowledge both in the image space and in the feature space. The interactive tool strictly correlates the views of data in both spaces. The effect of the change done in one space can be seen in the other. For example, the user can merge or split the clusters in the feature space and observe it result in the image space.

We have starting to validate the clinical significance of our segmentation system through a comparison (in time and reliability) with manual segmentations performed by medical specialists.

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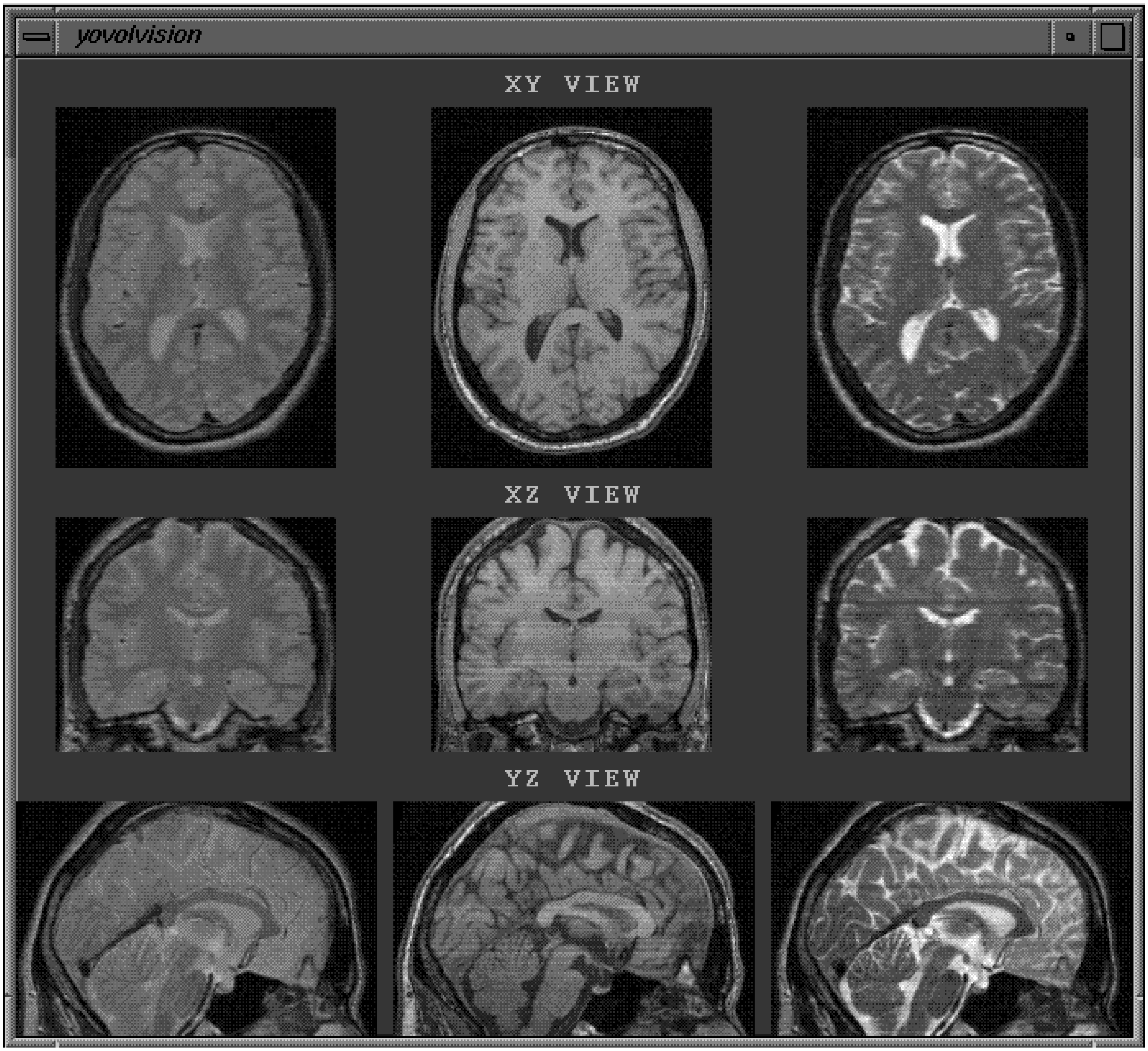

Fig. 1

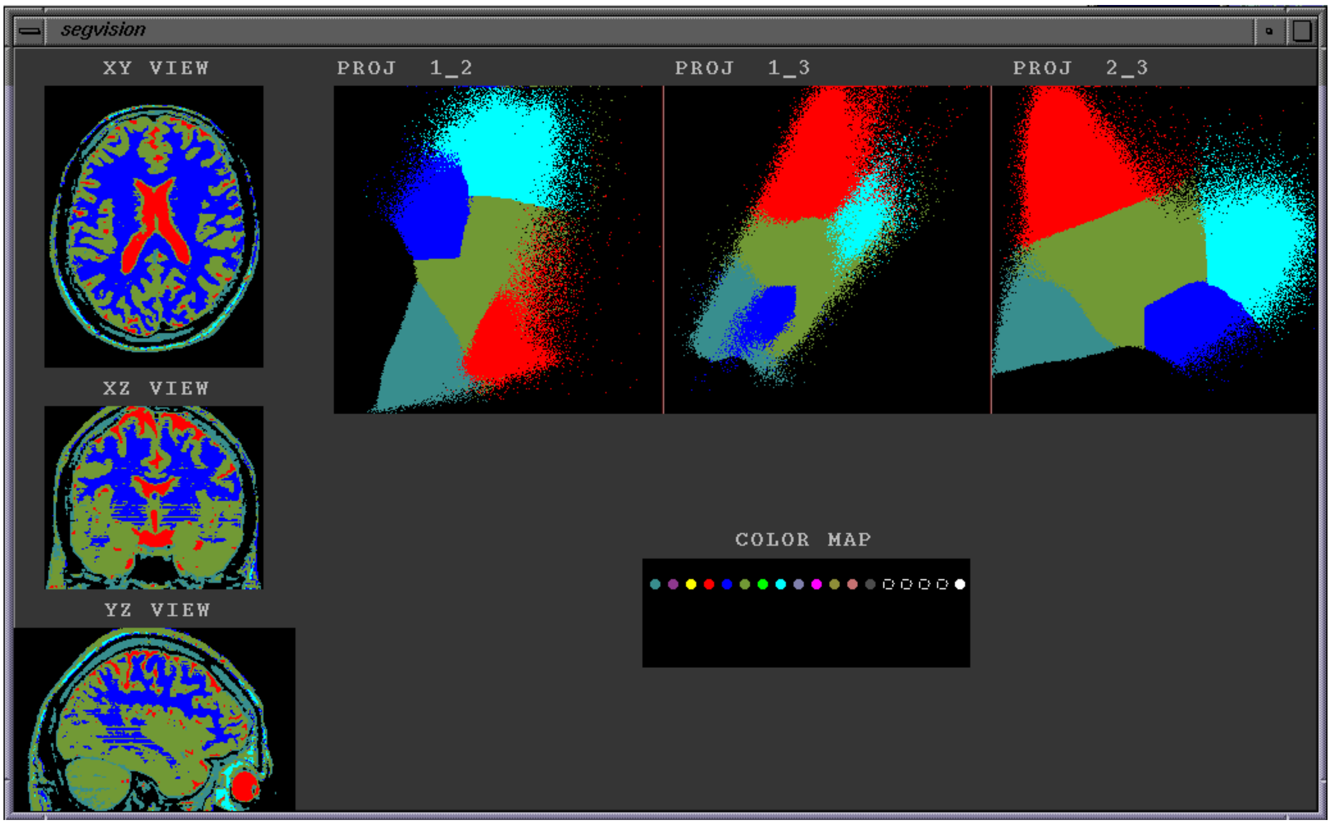
segvision
XY VIEW
PROJ 1_2
PROJ 1_3
PROJ 2_3
XZ VIEW
YZ VIEW
COLOR MAP

Fig. 2