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AN "ADAPTIVE RESOLUTION" ANALYSIS OF MULTIVARIATE MEDICAL IMAGES VIA UNSUPERVISED NEURAL NETWORK BASED CLUSTERING

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Abstract

A number of different diagnostic methodologies are provided by medical imaging technology, ranging from CT,MRI, SPECT, PET etc. A system for the segmentation of multivariate image volumes in the field of medical imaging is presented. The following steps are considered in the analysis sequence: unsupervised data clustering, point classification, and interactive post-processing refinement. In particular, the user can refine and even modify the segmented volume, according to its expertize and knowledge of the problem at hand by using a number of powerful facilities provided by the system graphic interface. The principal step in such segmentation sequence is the definition of clusters within the feature space. Anatomical or functional structures can be described both by small clusters with high probability density, and by large clusters with low probability density. Therefore, our proposal is a self-organizing neural network which is able to learn data clustering in an adaptive way, taking into account, within certain limits, the local density characteristics of the point-distribution. We call this property adaptive resolution clustering. The network combines standard competitive self-organization of the weight-vectors with a non-linear mechanism, called "Capture Effect", for the adaptive local modulation of the receptive field of each neuron.
A real data experiment is presented which shows the potentialities of the system.

1 Introduction

In the field of the analysis of multivariate medical imaging, the clustering approach to the segmentation plays now a central role (see [1] for a review). In the Pattern Recognition nomenclature, the clustering algorithms form a class of unsupervised methods which are alternative to the supervised classification methods. Supervised methods has been largely employed in medical imaging segmentation studies but provide for conditions hardly satisfied in the clinical environment. They require a very time consuming labelling of prototypical samples which a generalization process can start from. This way, the number of clusters must be predefined, and bias can be introduced by users due to the large inter-user variability generally observed when manual labelling is performed. On the contrary, unsupervised approaches self-organize the implicit structure of data and make clustering of the feature space indipendent from the user-dependent definition of the training regions. Nevertheless supervised techniques have been favored over unsupervised techniques because they can be used interactively, leaving the user in control of the final segmentation. From these considerations, interactive tools supporting an unsupervised clustering method has been our choice for combining the two approaches in order to attain better results.

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The analysis of multivariate medical images needs further considerations due to the particolarity of their data distribution. In particular, we notice that anatomical or functional structures can be described, in the feature space, both by small clusters with high probability density and by large clusters with low probability density. Thus, in the image space, strictly defined regions as well as very noisy regions can emerge. In the feature space, again, it means that structures can appear at different levels of resolution. An effective cluster analysis of multivariate medical images should therefore fit accurately such different resolutions in the distribution of density.

In this context, our proposal is a system which involves both the aspects just mentioned: (1) an high performance processing tool, whose core is a clustering algorithm implemented on a self-organizing neural network, for classifying points within the multidimensional feature space; (2) a powerful interactive interface by means of which the user is able to refine or even partly modify the segmented image provided by the system, by using his/her expertize. In particular, the system implements a self-organizing neural network, called "Capture-Effect" Neural Network (CENN) [3] [2]. During the learning phase the network self-organizes in such a way that a certain number of clusters are autonomously discovered and the partition of data which comes out from the learning phase takes into account the natural scale of spatial density the clusters emerge within the distribution of data. This is accomplished by the adaptive local modulation of receptive fields centered on neurons.

We'll show in this contribution that the segmented image which results from the CENN clustering can be considered a "comfortable" starting point for the user in the subsequent interactive refining phase. Some experimental results are presented to show the potentialities of the system.

2 The model of the Capture-Effect Neural Network

The Capture-Effect Neural Network (CENN) [3] [2] combines the model of soft-competitive self-organization of the neural prototypes (or weight-vectors) [4] [5] with a non-linear mechanism of adaptive local modulation of spherical Receptive Fields (RFs). By considering Gaussian neural units [4], the radius r_i of the (spherical) RF of the unit $\mathcal{N}_i$ can be defined as the width parameters of the Gaussian, but, more precisely, they can be defined as the limit distance from the corresponding center (which is the corresponding prototype $\vec{w}_i$) for which the Gaussian response $\gamma(d_i)$ becomes smaller then an arbitrarily fixed threshold $\varepsilon << 1$: $(r_i \ : \ \gamma(d_i) < \varepsilon \ , \ \forall \vec{x} \ : \ d_i > r_i)$. The mechanism of local adaptive modulation of the RFs is constituted by the updating rule by which the RF radius r_i of each neuron is adjusted according to the characteristics of the density of input data locally around the RF itself. All the RF radii are initially setted to a large value R_0 in such a way that all the units are initially broadly tuned ; subsequently, each RF radius is updated through the following rule:

$$\Delta r_i = s(k) \quad , \quad k = \eta(d_i - r_i)e^{-d_i/p} \ , \tag{1}$$

where $\eta \in (0,1)$ is the learning-rate factor and $p > 0$ is the parameter of the exponential factor. The function s is linear ($s(k) = k$) when $d_i < R_0$ and saturates to R_0 otherwise; thus, R_0 is used not only as the initialization value but also as the saturation limit for all the RF radii in the network, in such a way to fix a limit for the neurons which eventually should tend to become as broadly tuned as to cover a large part of the entire feature-space.

If conditions of stationarity of input data hold, each RF radius reaches a statistical equilibrium value which is related to the fact that the samples which fall inside the RF ($d_i < r_i$) tends to be balanced by the samples which fall outside ($d_i > r_i$). Thus, the equilibrium expresses the radial dispersion of the samples around $\vec{w}_i$, limited to an area of "attention" expressed by the parameter p. Therefore, in order to make sure that the equilibrium of each RF radius expresses the density of the input data distribution at the local level, the value of p must be chosen in the proper way. The authors have shown [2] that a good choice for p is $p = \hat{d}/D\ln 10$, where $\hat{d}$ is the mean Euclidean distance among all the neurons and the current input pattern and D is the dimension of the feature-space. In conclusion, the mechanism of adaptive local modulation of the RFs is responsible for the development of locally tuned units, whose RF sizes are well adapted (in a completely unsupervised way) to the density of data locally around the corresponding prototypes.

3 The clustering algorithm

The property that the equilibrium states of RFs are strongly related to the local density of data has been used by the authors of the CENN for developing an algorithm of data clustering, to be executed at the end of the learning phase, which is able to take into account, within certain limits, the scale of density (or level of

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spatial resolution) of the natural clusters which emerge in the feature-space (this property has been called by the authors "adaptive resolution clustering"). The clustering algorithm is as follows. The units which have not their RF radius saturated at the value R_0 (see (1)), that is the locally tuned units, are collected into different groups (or neural clusters) according to the degree of overlapping of their RFs: two units $\mathcal{N}_i$ and $\mathcal{N}_j$ are considered to belong to the same group $\mathcal{G}$ if the following rule holds :

$$\| \vec{w}_i - \vec{w}_j \| < (r_i + r_j)\sigma , \tag{2}$$

where $\sigma \in (0, 1)$ is the degree of overlapping of the RFs. In this way we obtain K groups of units, $\mathcal{G}_k, k = 1, ..., K$, and some unit may be present in more then one group. Grouping conflicts are solved by assigning each unit shared by two or more groups to the group in which the average RF size (computed among all the non-shared units of the group) is the closest to the RF size of the shared unit.
Following the clustering algorithm, every test vector $\vec{x}$ is classified by exploiting the winner-take-all rule in the following way:

$$\vec{x} \in (k^{th}\ cluster) \ \ if \ \ z = \arg\min_j \frac{\| \vec{x} - \vec{w}_j \|}{r_j} \ \ , \ \ \vec{w}_z \in \mathcal{G}_k \ . \tag{3}$$

In such a rule the distances between the current input vector $\vec{x}$ and the prototypes $\vec{w}_j$ are weighted by the corresponding RF radius r_j, in such a way that the vectors $\vec{x}$ which fall nearly in the middle between two prototypes are assigned to the units with the broader RF. This corresponds to a Bayesian classification strategy applied at a local level; in fact, the equilibrium value of the RF radii can be considered as a kind of estimation of local radial variance within the input data distribution.
In our system the choice of the parameter σ is left to the user. Such a parameter can be viewed as a general design parameter which is at disposal of the user on the basis of the a priori knowledge of the task

4 The interactive user interface

The characteristics of the model lead to a segmentation map, fully unsupervised, that often can be already considered a satisfactory final result. Otherwise, the user can utilize its general expertize and its specific knowledge of the problem at hand for refining or even slightly modifying the segmentation map which results from the application of the CENN clustering procedure. Interactive correction of clusters identification can be performed in the feature space, after the unsupervised training, by using scatter plots. That is, by examining bidimensional projections of the feature space, named scatter plots, clusters can be selected and modified, via mouse, allowing the user to introduce his/her own knowledge in clustering, starting from unsupervised preliminary results. After the generalization of training by coding algorithms, a further interactive correction of cluster identification can be made in the so defined image space and clusters can be suppressed and merged or even modified (automatically or manually) by adding or removing voxels in clusters. Some examples of the use of the interactive user interface are shown in the following section.

5 An example

We present an example where the system is tested on a set of brain MRI images in order to obtain a segmented image. Three volumetric data sets representing T1-, T2- and proton density- weighted MRI data of a healthy volunteer have been used, coming from the Montreal Neurological Institute (MNI) at the McGill University. Figure 1a,b,c shows a sagittal view of the volumetric data. The goal was to discriminate pixels from different tissues such as white matter, grey matter, cerebrospinal fluid, fat and skull for defining a software-based phantom of the head. Data were considered by averaging the grey levels over 3x3 squared neighboroods around each pixel, in order to smooth the pixel noise. The segmented image directly produced by the CENN is shown in Figure 1d. A comparison with the result of a standard k-means algorithm is then presented (Figure 1e). Classified regions in the CENN segmented image are defined more precisely then in the k-means one; thus, the CENN result can be considered a "comfortable" starting point for further refinements by the user. Two examples of postprocessing refinement by the user are shown in Figures 1f (merging of two classes) and 1g (elimination of little spots of noisy pixels). Finally, in Figure 2 are shown the three scatter plots related to the three 2D projections of the 3D feature-space. The circles represent the groups of neurons (whose weight prototypes are represented in the scatter plots by little black squares) formed by the clustering algorithm: the radius of each circle is calculated by averaging over the radii of the neurons of the corresponding group, and the centre of the circle is the baricentral position among the same neurons. The property of "adaptive resolution clustering" of the network can be observed by noting that the prototypal radii are well adapted to the local density of data.

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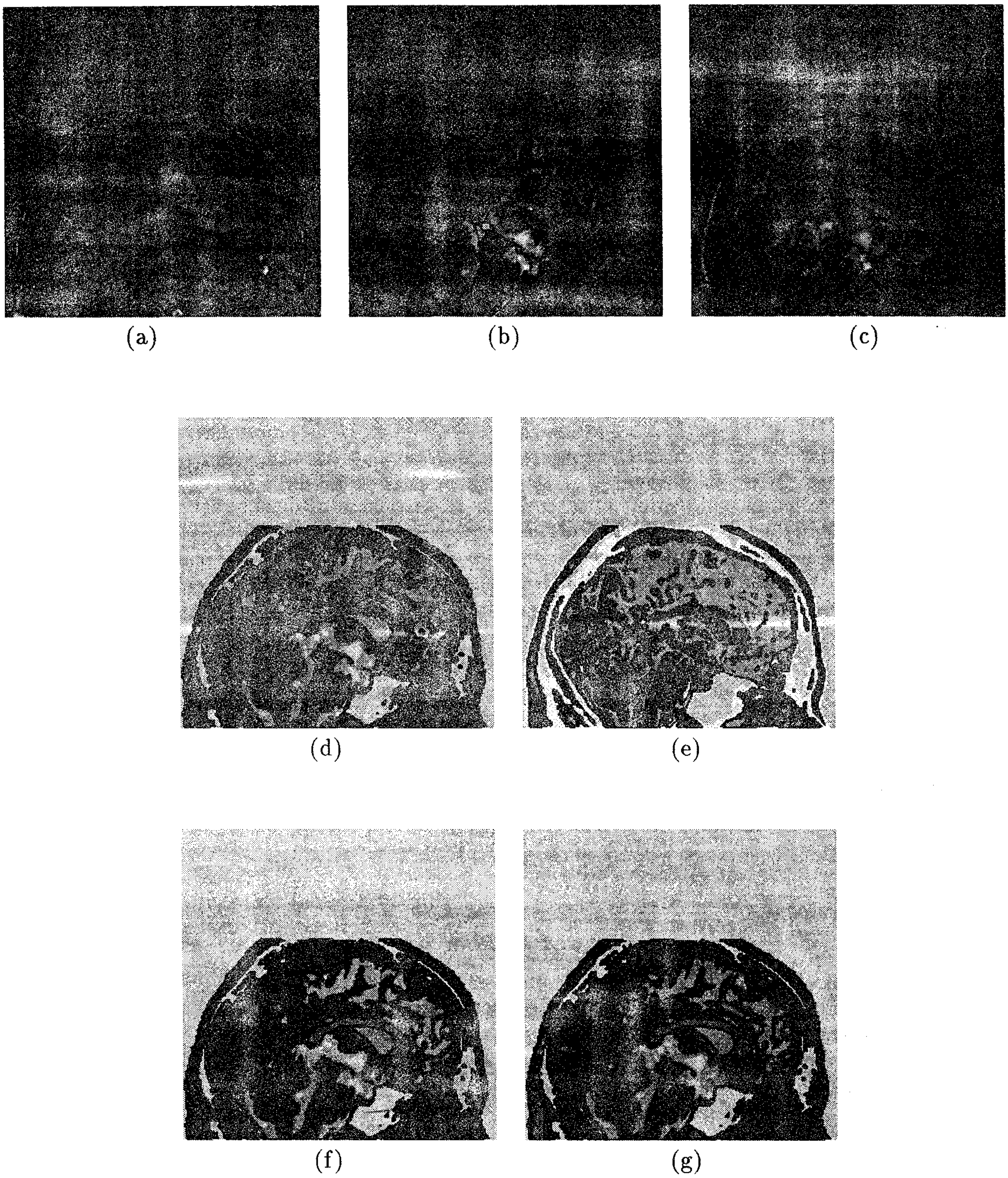

Figure 1: Sagittal views of (a) T1-, (b) T2- and (c) Proton Density- weighted MRI data (courtesy of MNI). (d) Segmentation map by the CENN clustering. (e) Segmentation map by the standard k-means algorithm. (f) Interactive tool: two classes in the upper-left region of the head are joined together (via mouse) in order to achieve better definition of the grey-matter region. (g) Interactive tool: noisy spots are eliminated (via mouse) in the lower-left region of the head

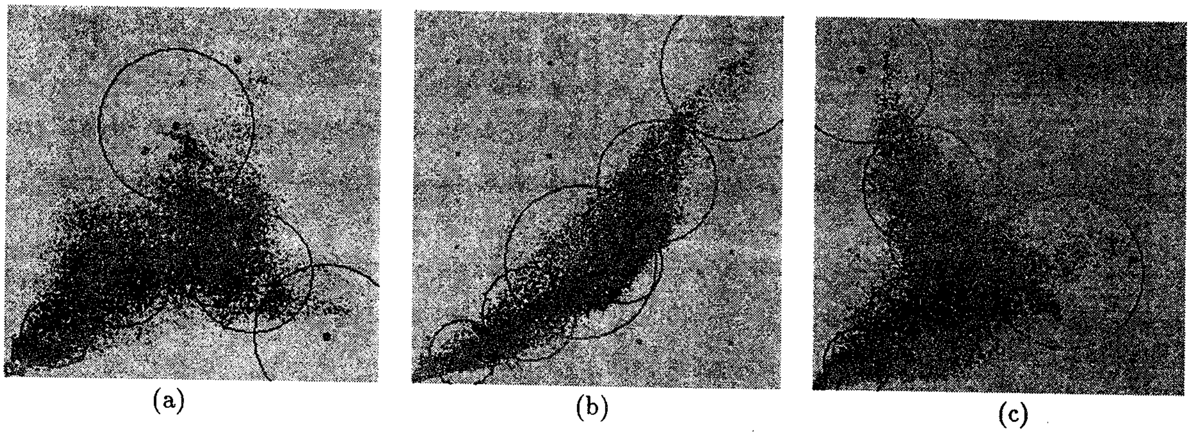

Figure 2: Scatter plots of data and CENN clustering in the feature-space. Projections onto: (a) the T1 and T2 axes, (b) the T1 and Proton Density axes and (c) the T2 and Proton Density axes. The grey dots are data points. The little black squares are the neural prototypes. The circles represent the groups of neurons formed by the CENN clustering algorithm (see text).

6 Conclusions

A system for the processing of multivariate image volumes in the field of medical imaging has been presented. The core of the system is the Capture-Effect Neural Network which operates under the self-organizing learning paradigm. The CENN performs unsupervised classification (or clustering) of multidimensional data with the property of taking into account the scale of spatial density of the natural clusters of data. The CENN clustering procedure has been used in the system for producing a segmented volume from a multivariate volume. Thanks to the property of the CENN, the segmented image resulted a very "comfortable" starting point for the user for further detailed investigations, which have been favored by introducing in the system a powerful interactive graphic interface.

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