Frontiers in Artificial Intelligence and Applications

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Advances in Intelligent Systems

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Intelligent Systems can be defined as systems whose design, mainly based on computational techniques, is supported, in some parts, by operations and processing skills inspired by human reasoning and behaviour. In a wide sense, also animals, such as bats and flies, show behaviour which appears to be extremely interesting from a machine viewpoint. Machine intelligence experts' might say that the machine IQ can be improved by implementing this behaviour. Actually, for a machine, intelligence would imply actions like reduction of data throughput, fast data interpretation, and data compression, extraction of features, recognition of special patterns, de-noising, prediction, simulation of human decision making, treatment and exploitation of uncertainty and imprecise information. Intelligent Systems must typically operate in a scenario in which non-linearities are the rule not a disturbing effect to be corrected. Finally, Intelligent Systems also have to incorporate advanced sensory technology in order to simplify man-machine interactions.

Several algorithms are currently the ordinary tools of Intelligent Systems: genetic, evolutionary and immune algorithms and strategies, approximate reasoning, fuzzy logic and, of course, Neural Networks. All of these innovative computing techniques evolve and increase in importance independently but have as a common background the idea that exact as well as precise solutions are often not the response to practical requirements. A neologism was coined which embodies the above mentioned different techniques and approaches: Soft Computing. Using Lotfi Zadeh's words, who is the Honorary Chairman of our Symposium: the guiding principle of Soft Computing is to exploit the tolerance to imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost.

This is strongly in contrast with the claims of Artificial Intelligence, which has based its popularity as well as its decline, on manipulation of symbols, decision trees and hard logic. Unfortunately, the most important scientific problems are ill-posed, lack of data strong, they don't often have a unique solution, and in some cases, an important information is related to the possibility of managing different solutions with different degrees of reliability. Selecting one possible solution among many is not very reasonable, particularly in view of practical applications, which call for measurable results and strategies which can be anything but theoretically elegant, (e.g. ill-posedness of a task, which may come from a limited number of measured data and intrinsic inaccuracy of the methodologies: a priori knowledge on physical facts introduced as regularization techniques may yield important constraints to include in the inverse mapping for overcoming the ill-posedness).

Actual signal processing calls for coping with conflicts which commonly inhibit further actions during numerical computation. Conflicts paralyse actions and thus must be avoided in standard numerical computation; however, they often represent important information about a problem and their correct interpretation can lead to robust and high quality solutions. A trivial example is the search for a global minimum among different local minima in competition.

In this sense, Intelligent Systems are pervasive. Artificial Neural Networks have attracted an enormous interest in recent years. They surely yield a framework for implementing several different approaches. From a research perspective, the main limitation, highlighted by a huge amount of incompetent works, is its ambiguous way of forming concepts and solutions. Industrial partners and leading research groups ask for clarifications and opening black boxes. On the other hand, scientists are frequently asked why they leave an algorithm to run and play blind man's buff to extract from clues just obvious and expected concepts. Why not include prior knowledge, if available? Financial applications are an important example of this. Fuzzy systems are the answer. They are extremely

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useful when it is possible to articulate qualitative knowledge in fuzzy if-then rules. They have revolutionised the market of appliances and consumer electronics.

This book contains a selection of papers presented at the AMSE-ISIS'97 Symposium on Intelligent Systems. Authors came from all over the world and brought their expertise to Reggio Calabria.
This Symposium continues and follows up the series of International Symposia organized by AMSE, SIGEF and BUFSA. This is indeed the tenth in this series of scientific events. Previous events were held in Istanbul (1988), Brighton (1989), Cetinje (1990), Warsaw (1991), Geneva (1992), London (1993), Lyon (19949, Brno (1995) and Leon (1996). Future events are foreseen in Melbourne and Lyon.
For the selections of the papers to be presented at the Symposium, the International Scientific Committee appointed a select International Refereeing Committee. Their cooperation and competent work is heartily acknowledged.
The Organising Committee is also indebted to the members of the Local Committee for the assistance received in making major decisions.

Various special interest sessions have been planned to allow experts in diverse fields to meet and to exchange their ideas on: Applications of Intelligent Systems in Modelling and Prediction of Environmental Changes, Cellular Neural Networks for NonLinear Filtering, NNs for Signal Processing, Image Processing, Transportation Intelligent Systems, Intelligent Techniques in Power Electronics, Applications in Medicine and Surgery, Hardware Implementation and Learning of NNs, Several plenary talks by world renowned experts have also been planned, which offer an insight in major world Laboratories.
The relevant and growing interest is confirmed by the adhesion and sponsorship of IEEE Neural Network Council and INNS Special Interest Groups. Several Italian Associations have given their support to the organisation: SIREN, IIASS, Fondazione Bonino-Pulejo, AEI, Elsag Bailey. We heartily acknowledge their enthusiastic participation.

The organization of an International Symposium requires the efforts of several people. I would like to express my gratitude to everyone that has been involved in this effort, by generously offering their commitment, energy and spare time to make this event a successful one.

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A NEURAL BOOTSTRAP FOR THE POSSIBILISTIC C-MEAN ALGORITHM

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Abstract. In this article, we present an application of possibilistic approach to clustering to the segmentation of multivariate images. This approach relaxes the *probabilistic* constraint on the membership functions of points in clusters or the degrees of *typicality* of points. We use a formulation of the Possibilistic C-Means (PCM) algorithm proposed by Krishnapuram and Keller and experiment a robust neural bootstrap algorithm based on the Capture Effect Neural Network in order to improve stability of results and avoid the estimation of some critical parameters of PCM. The quality of the obtained results is higher than using methods using probabilistic constraints.

1 Introduction

The possibilistic approach to clustering [7, 8] assumes that the membership function or the degree of *typicality* of a point in a *fuzzy* set (or cluster) is absolute, in the sense that it does not depend on the membership values of the same point in other clusters contained in the problem domain.

By contrast, many clustering approaches impose a *probabilistic constraint*, according to which the sum of the membership values of a point in all the clusters must be equal to one. As a consequence, C-Mean (CM) [5], Fuzzy C-Mean (FCM) [4], Maximum Entropy Principle based Fuzzy Clustering (MEP-FC) [11, 3, 10], and many other clustering methods assuming the probabilistic constraint cannot generate membership functions whose values can be interpreted as degrees of typicality.

In [7, 8], Krishnapuram and Keller presented two versions of a Possibilistic C-Mean (PCM) algorithm that avoids the assumption of the probabilistic constraint.

While clustering algorithms based on the probabilistic constraint perform primarily a partition of the given data set, the PCM is a mode-seeking algorithm, i.e. each component obtained by the PCM correspond to a dense region in the data set [8].

The first method proposed by Krishnapuram and Keller [7] (PCM-I) is based on a modification of the objective function of FCM [4]. In this case, one must supply the values of some parameters such as the m, that is a *fuzzifier parameter*, and others regulating the weight of the spread of membership functions [7, 2].

In [8], Krishnapuram and Keller suggested an alternative formulation of Possibilistic C-Mean (PCM-II) based on modification the cost function of CM [5] (instead of the FCM), avoiding, in this way, the determination of the fuzzifier parameter.

In this article we propose a new method based on application of the Capture Effect Neural Network (CENN) [6] to the data set, in order to obtain a robust estimation of the spread of membership functions. Moreover we present an application of the developed algorithms to the segmentation of multivariate medical images [12, 9].

In the next two sections, the two versions of the PCM are presented. In Section 4 we present the application of CENN to the bootstrap step of the PCM. In Section 5 we describe the Magnetic Resonance Images (MRI) used in our test. Section 6 presents and discuss the experimental results. Conclusions are given in Section 7.

2 Possibilistic C-Means - First Formulation

The Possibilistic C-Means (PCM) [7, 8] is based on the relaxation of the probabilistic constraint in order to interpret in a *possibilistic* sense the membership function or *degree of typicality* $u_{jk} \in [0,1]$ of the k-th point to the j-th cluster.

Let $U = [u_{jk}]$ be the *fuzzy membership matrix*, n the dimension of the data set, and c the number of clusters. In the PCM, the elements of U fulfill the following conditions:

$$u_{jk} \in [0,1] \quad \forall \; j,k; \tag{1}$$

$$0 < \sum_{k=1}^{n} u_{jk} < n \quad \forall \; j; \tag{2}$$

$$\bigvee_{j} \; u_{jk} > 0 \quad \forall \; k. \tag{3}$$

The relaxation of the probabilistic constraint allows an interpretation of the membership function in a possibilistic way, and permits the function to be contained in the whole hypercube, rather than in the hyperplane defined by the constraint.

The cost function of the first formulation of the PCM [7] (PCM-I) is a modification of the objective function of the FCM model, with the addition of a term to *force* the values u_{jk} to be greatest as possible, in order that points with a high degree of typicality with respect to a cluster may have high u_{jk} values, and points not very representative may have low u_{jk} values in all the clusters:

$$J_m(U,\mathbf{Y}) = \sum_{k=1}^{n}\sum_{j=1}^{c}(u_{jk})^m E_j(\mathbf{x}_k) + \sum_{j=1}^{c}\eta_j \sum_{k=1}^{n}(1-u_{jk})^m, \tag{4}$$

where :

- $X = \{\mathbf{x}_1, ..., \mathbf{x}_n\}$ unlabeled samples;
- $Y = \{\mathbf{y}_1, ..., \mathbf{y}_c\}$ cluster centers;
- $E_j(\mathbf{x}_k) = \|\mathbf{x}_k - \mathbf{y}_j\|^2$ square of the Euclidean distance;
- $m \in (1, +\infty)$ *fuzzifier* parameter;
- η_j distance over which the membership value in the j-th cluster becomes equal to .5.

It is worth noting that if the second term of $J_m(U,\mathbf{Y})$ is omitted, the elimination the probabilistic constraint leads to a trivial solution of the minimization of the remaining cost function, that is $u_{jk} = 0 \; \forall j,k$.

The value of the parameter η_j depends on the distribution function of each cluster. If one searches for clusters with similar distribution, η_j could be assumed to be the same for each cluster. In general, it is assumed that η_j depends on the average size and on the shape of the j-th cluster.

Moreover the value of η_j weights the contribution of the second term of the objective function with respect to the first term. If one assumes that the two terms have the same importance, the value of this parameter should be on the order of $E_j(\mathbf{x}_k)$.

As demonstrated by Krishnapuram and Keller [7], the couple $(U,\mathbf{Y})$ minimizes J_m, under the constraints (1-3) only if:

$$u_{jk} = \frac{1}{1+\left(\frac{E_j(\mathbf{x}_k)}{\eta_j}\right)^{1/m-1}} \qquad \forall \; j,k \tag{5}$$

and

$$\mathbf{y}_j = \frac{\sum_{k=1}^{n}\mathbf{x}_k \; u_{jk}}{\sum_{k=1}^{n} u_{jk}} \qquad \forall \; j. \tag{6}$$

This theorem provides the conditions need in order to minimize the cost function $J_m(U,\mathbf{Y})$. Such conditions can be interpreted as formulas for recalculating the membership functions and the cluster centers.

A bootstrap clustering algorithm is anyway needed before starting PCM in order to obtain an initial distribution of prototypes in the feature space and to estimate some parameters used in the algorithm.

Considering an FCM bootstrap for PCM, the following definitions of η_j are used [7, 8]:

$$\eta_j = K\frac{\sum_{k=1}^{n}(u_{jk})^m E_j(\mathbf{x}_k)}{\sum_{k=1}^{n}\sum_{j=1}^{c}(u_{jk})^m} \tag{7}$$

$$\eta_j = \frac{\sum_{x_k \in (\pi_j)_\alpha} E_j(\mathbf{x}_k)}{|(\Pi_j)_\alpha|} \tag{8}$$

where $(\Pi_j)_\alpha$ is the set of points of the j-th cluster whose membership functions is above a given threshold α (α-cut). The first definition makes η_j proportional to the mean value of the *intracluster distance*, and critically depends from the choice of K (in [7] is has been suggested $K = 1$). The second definition makes η_j proportional to the mean value to the intracluster distance calculated by using those belonging to the α-cut.

The PCM starts from the solutions of the boostrap clustering algorithm and is based on two Lloyd-Picard iterations, the first one using Eq. 7, and the second using Eq. 8 [7, 1].

3 Possibilistic C-Means - Second Formulation

In [8], in order to avoid the estimation of the fuzzifier parameter m, Krishnapuram and Keller proposed an alternative formulation of the PCM based on the following modification of the objective function of the CM [5] (PCM-II):

$$J_m(U, \mathbf{Y}) = \sum_{k=1}^{n}\sum_{j=1}^{c} u_{jk}E_j(\mathbf{x}_k) + \eta_j \sum_{k=1}^{n}(u_{jk}\log u_{jk} - u_{jk}). \tag{9}$$

For this $J_m(U, \mathbf{Y})$ the prototype update equation is unchanged (Eq.6), while it can be shown that the update equation for u_{jk} is:

$$u_{jk} = \exp\left\{-\frac{E_j(\mathbf{x}_k)}{\eta_j}\right\} \qquad \forall\ j, k. \tag{10}$$

The PCM algorithm is unchanged, with the exception of using Eq. 10, instead of Eq. 5.

4 Application of the Capture Effect Neural Network

The Capture Effect Neural Network (CENN) [6] is a self-organizing neural network able to take into account the local characteristic of the point-distribution (*adaptive resolution clustering*). CENN combines standard competitive self-organization of the weight-vectors with a non-linear mechanism of adaptive local modulation of receptive fields (RF) of neuron (*Capture Effect*). The learning of CENN is composed by two steps:

- **training step** where an abundant number of prototypes is used (defined by their weight vectors and RF dimension) for vector quantization of data;
- **clustering step** where prototypes are grouped in order to represent the cluster distributions.

After learning:

- the distribution of the prototypes in the feature space approaches the optimal vector quantization scheme of the distribution of input data, that is approximates the mixture probability density function;
- the radial size of the RF of each neuron reaches a stable value which is strongly related to the spatial density of input data locally around the center of the RF itself, that is the weight-vector of the neuron.

It is worth noting that the clustering step of CENN gives automatically a robust estimation of the number c of centroids and of their coordinates $\mathbf{y}_j$ and radii r_j. Moreover we can assume that $\eta_j = f(r_j)$.

As a consequence it seems useful to use the CENN instead of the FCM as a bootstrap for PCM. In this way we obtain the following new version of the PCM:

Possibilistic Neuro-Fuzzy C-Means (PNFCM) algorithm

- Neural Bootstrap
  - *train and clusterize the Capture Effect Neural Network and obtain* c, η_j, *and* $\mathbf{y}_j^0$;
  - *compute* $U^{(0)}$ *using Equation 10;*
  - *set the iteration counter to* $l = 0$ *and the stop parameter* ϵ.
- Possibilistic C-Means

  Repeat
  - *update the prototypes* $\mathbf{y}_j^{(l+1)}$ *using Equation 6;*
  - *compute* $U^{(l+1)}$ *using Equation 10;*
  - *increment* l;

  Until

  $\bigvee_j \|\mathbf{y}_j^{l+1} - \mathbf{y}_j^{l}\| \le \epsilon$

5 Experimental Data Set

We applied the PNFCM to the segmentation of different tissues (white matter, gray matter, cerebrospinal fluid, skull, eyes, etc.) using Magnetic Resonance Images (MRI) of the head. In particular, three volumetric data sets representing T1-, T2-, and PD-weighted MRI data of a healthy volunteer were used (see Fig.1). No corrections were made to reduce the inter-slice variability of image intensity.

The fusion of the data sets produced a three-variate volume. Each triplet of voxel intensity in the volume was represented by a point in a 3D feature space, whose coordinates represented the intensity values in that voxel of each volume belonging to the multivariate volume.

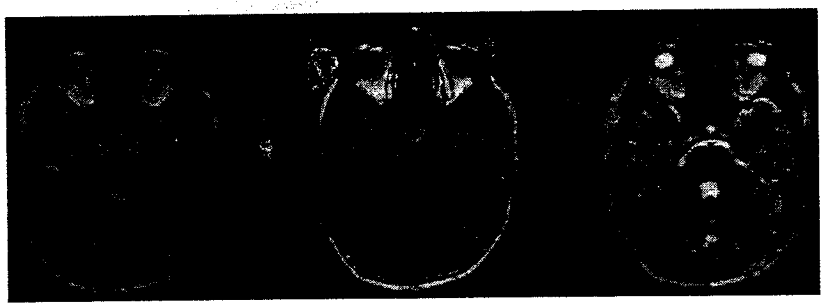

Figure 1: T1-, T2- and proton density- weighted MRI data.

6 Methods and Results

In Fig. 3 the clusters obtained by CENN in the three-dimensional feature space, are shown. The application of this neural network to the data set gives as a result the number c of centroids and of their coordinates $\mathbf{y}_j$ and radii r_j. In our experiments we found a good evaluation of η_j as

$$\eta_j = \sqrt[D]{r_j} \ , \tag{11}$$

where D is the dimensionality of the feature space.

After the neural bootstrap with CENN, the PCM step was performed, using $\epsilon = 0.01$ as stop parameter. The obtained partition of the feature space is showin in Fig. 4.

In Fig. 2 the clusters obtained with the FCM are shown, while in Fig. 5, the result of segmentation with our PNFCM algorithm is compared with those obtained applying FCM and CENN alone.

One can notice that the PNFCM algorithm improves the results of its bootstrap based on the CENN algorithm and gives better results than the standard FCM algorithm. In particular PNFCM reduces the number of clusters from CENN and obtains a more precise correspondence with real tissues. Moreover, in comparison with FCM, PNFCM gives better results for brain tissues and is able to find the cerebrospinal fluid and eyes cluster.

Figure 2: FCM algorithm: projections of clusters (obtained in the 3-D feature space) on planes T1-T2, T1-PD, and T2-PD.

Figure 3: CENN algorithm: same as Fig. 2.

Figure 4: PNFCM algorithm: same as Fig. 2.

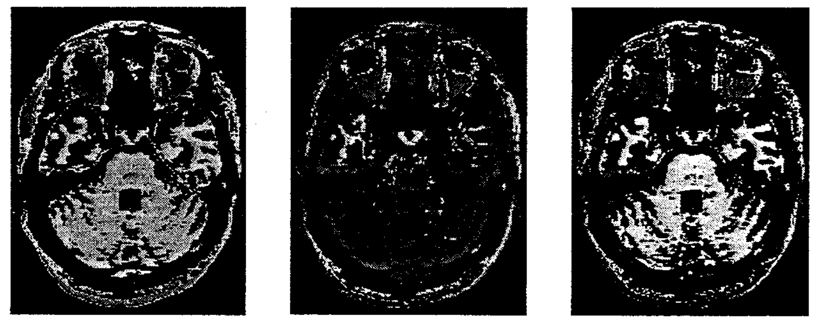

Figure 5: Segmentations obtained by the FCM, CENN, and PNFCM.

7 Conclusions

In this article, we have presented the application of possibilistic approach to clustering to the segmentation of multivariate images. In this approach, the probabilistic constraint is relaxed. As a result the obtained degrees of *typicality* turn out to be absolute, in that it does not depend on the membership values of the same point in other clusters.

We use a formulation of PCM [8] that avoids the critical estimation of the fuzzifier parameter m. Moreover, a more robust neural bootstrap algorithm, based on CENN [6], has been used in order to improve stability of results by avoiding the estimation of other critical parameters that regulate the weight of the spread of membership functions [7, 2].

The final quality of the results of our algorithm applied to the segmentation of medical multivariate images is higher than using methods using probabilistic constraints.

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Application of fuzzy logic to visual system modeling

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Abstract. A fuzzy logic algorithm was used to describe the processing of the information in the invertebrate visual system. The three-input and one-output model was applied to get a characterization of the dipteran electroretinographic response to different illumination conditions. A conditioned weighted sum was provide to express the spectral sensitivity maxima of the fruitfly compound eye as well as a special amplifying phenomena localized in the neural cells from the lamina ganglion.

Key words: fuzzy algorithm, electroretinogram, visual system

1. Introduction

The complex systems from nature, either physical or biological systems, are often evolving on the basis of some complicated laws which are difficult to approximate in the classical mathematics. Such a system can be considered the visual analyzer in the invertebrates, representing a very convenient material for the study of the visual information processing in the living world. Characterized by an intermediate grade of complexity, the arthropods, and especially the dipteran, visual system organization is somewhat parallel to those of the vertebrate visual analyzer while its set of neurons is more limited and easier to identify [1]. Due to its features of un-predictability and imprecision the fuzzy logic is rather suitable to describe the responses to well controlled external conditions. The aim of this article is to give a generalization of the numerical results