CLASSIFICATION TECHNIQUES FOR FEATURE EXTRACTION IN LOW RESOLUTION TOMOGRAPHIC EVOLUTIVE IMAGES: APPLICATION TO CEREBRAL BLOOD FLOW ESTIMATION

Marie CHAN, Unité 230 INSERM,Toulouse
Joseph AGUILAR MARTIN & **Nuria PIERA**, LAAS du CNRS, Toulouse
Pierre CELSIS & **Jean Pierre MARC-VERGNES**, Unité 230 INSERM,Toulouse

RESUME

Pour améliorer les performances de la méthode de la variable instrumentale dans le calcul du debit sanguin cérébral régional au moyen d'un tomographe à émission de photon unique, et du traceur diffusible inerte ^{133}Xe, nous utilisons le Logiciel d'Analyse Multivariable de Données avec Apprentissage (LAMDA) pour classer les pixels des images de concentration locale de traceur. La méthode LAMDA distingue correctement les pixels intra et extra-cérébraux et reconnait ceux contaminés par la proximité de l'os et du passage d'air nasal. On peut conclure que cette méthode peut améliorer la fiabilité des images des débits estimés.

SUMMARY

In order to improve the performance of the instrumental variable method (IVM) in calculating regional cerebral blood flow (rCBF) using Single Photon Emission Computed Tomography (SPECT), and inert diffusible tracer such as ^{133}Xe, we use Learning Algorithms for Multivariate Data Analysis (LAMDA) to classify the pixels of the images of local concentrations in the brain. The LAMDA method correctly distinguishes between extra and intra-cerebral pixels and recognizes in these last the contaminatation by bone and air passage artefact . We thus conclude that LAMDA methods can improve the reliability of images of CBF estimates.

1 Description of the problem

The calculation of regional cerebral blood flow (rCBF) in humans using single photon emission computed tomography (SPECT), and inert diffusible tracer such as ^{133}Xe, is based on the information given by a sequence of images obtained at regularly spaced time instants. This sequence consists on 4 images spaced by 1 minute.After having completed an experience the data can be organized as a collection of 4-dimension vectors corresponding to the 4 measurement instants for each pixel.
The parameters of the clearance curve at each pixel of the image are directly related to the blood flow according to the now classical dynamic model given by the Kety equation.
Classical estimators as recursive least squares (RLS) and instrumental variable method (IVM) have been used. Nevertheless any attempt of improvement is faced with the impossible increasing of information because of the shortness of the sequence of images.
Statistical classification or clustering methods can be applied to obtain groups of similarity. Learning Algorithms for Multivariate Data Analysis (LAMDA) have been chosen because they do not need previous information about the number of classes.The LAMDA method, by using membership functions related to Fuzzy Set theory, can choose arbitrarily the connectives that combine the contribution of the components the choice of which adjusts the exigency or discrimination power of the algorithm. Thus the parts of the image that are simpler to detect will be identified and eliminated with low exigency so that the remaining items shall be properly gathered into significant similarity classes.
Our Tomomatic 64 provides 3 transverse slices of 2 cm thickness with an in-plane FWHM of 1.7 cm^2. For each slice, a sequence of 4 images spaced by 1 minute is reconstructed in a 32x32 matrix. Thus in a 4 minute experience, 4 images of each slice are obtained, and therefore for each pixel 4 radiometric values are available, they correspond to 4 observations of the clearance curve of the diffusible tracer in that point.

2 Dynamic equations of the activity of a diffusible radioactive tracer.

The parameters of the clearance curve at each pixel of the image are directly related to the blood flow according to the now classical dynamic model given by the Kety equation:

$$dC_i(t)/dt = [F_i C_a(t)/W_i] - [F_i C_a(t)/\lambda_i W_i]$$

Where $C_i(t)$ is the instantaneous local tissue tracer concentration in tissue i (cps/unit weight), and $C_a(t)$ is the instantaneous concentration in arterial blood, in practice it will be replaced by the pulmonary concentration curve commonly recorded, $B.C_p(t)$ where B is a proportionnality coefficient. λ_i is the brain blood partition coefficient for the tracer (ml.100 g^{-1}), F_i is the flow per unit tissue weight (ml.100 g^{-1} . min^{-1}) and W_i is the weight of the tissue (100 g). The clearance rate is $K_i=F_i/\lambda_i W_i$.
The concentration is observed at sample instants n=1,2,3,4 and therefore a discrete recurrent model can be deduced were $y(n) = C_i(n)$ and $u(n) = C_p(n)$ and the parameters to be estimated are α and β joined in the 2-vector θ.:

$$y(n) = \alpha.y(n-1) + \beta.u(n-1) + \varepsilon(n) , \quad \theta = (\alpha \ \beta)^T$$

3 Estimator equations.

Estimators of the family of recursive least squares (RLS) have been used. The instrumental variable method (IVM) is a well known generalization of RLS in the framework of pseudo inverses.The concept of instrumental variable may be applied to the dynamic model.The form taken by the equation for N instants is:

$$y(N) = h^T(N)\ \theta + \varepsilon(N) , \quad h^T(N) = [\ -y(N) , u(N)\ ]$$

The estimator is constructed with the instrumental matrix M(N) as follows:

$$\theta(N)=(M(N).H(N))^{-1}M(N).y(N)$$

For the least squares estimator $M(N)=H^T(N)$, whereas the IVM estimator is obtained choosing $M(N)=Z^T(N)$

$$Z^T(N) = [\ h^*(1),\ h^*(2),h^*(3),...h^*(N)\ ],$$
$$h^{*T}(N) = [\ -y(N-\delta) , u(N)\ ]$$

where Z(N), *delayed observations instrumental matrix* [2], is formed replacing h(N) by $h^*(N)$ that depends on an arbitrary delay δ, by these means the influence of correlations are avoided.The consideration of the correlations by the IVM [3] increases the goodness of the estimators, their performances remain insufficient because of the poor information given by so short sequences, particularly with N=4. Nevertheless any attempt of improvement is faced with the impossible increasing of information.

4 Classification of pixels.

Here is described an alternative method where a previous classification of pixels is performed in order to gather all similar measurement points with respect to the time profile of their clearance curve.

As shown in figure 1, each pixel has N, values associated to the clearance curve. After having completed an experience, the data can be organized as a collection of N-dimension vectors corresponding to the N measurement instants for each pixel. Therefore statistical classification or clustering methods can be applied in order to distribute the vectors into groups of similarity.

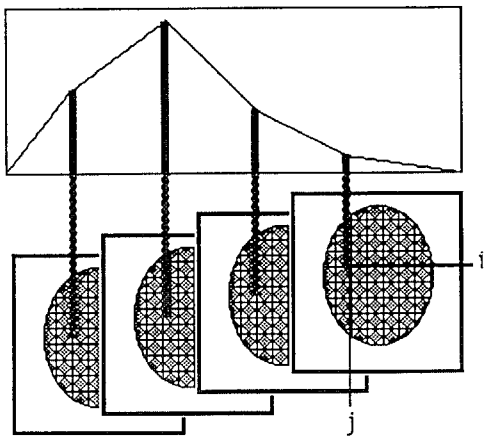


Figure 1

Learning Algorithms for Multivariate Data Analysis (LAMDA) have been chosen because they do not need previous information about the number of classes and several similarity measures can be investigated easily in order to adjust the selectivity of the algorithms. The principle of LAMDA algorithms can be described by figure 2, where the possibility of switching between supervised and self-learning is illustrated as well as the sequential property with respect to data.

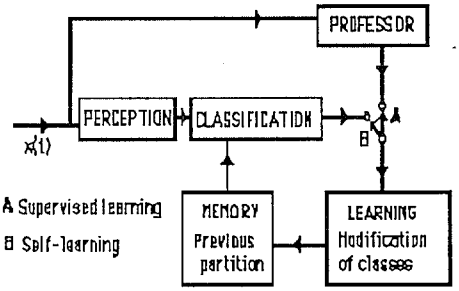


Figure 2

The LAMDA classification method is based on an iterative algorithm that takes sequentially the items, represented by N-dimension vectors, and evaluates their membership with respect to all the existing classes, $Cl_1, Cl_2, \ldots Cl_M$, plus an *empty class* Cl_0, then a decision procedure decides to assign the current analyzed item to the maximum membership class. The membership is computed from the observed values of the components of the vector x(t), and using the description parameters of each class. The contribution of each component is combined using "connective functions" related with the logical connectives in Boolean algebra, i.e. union and intersection. A particular feature of the LAMDA algorithms is to allow the introduction of mixed connectives depending of a parameter that adjusts the selectivity of it, and therefore determines the number of effective classes.
If Cl_0 was chosen a new class Cl_{N+1} shall be created by initializing it with the present item. By this procedure there is no need of knowing beforehand the number of classes or clusters.

Figure 3 is the algorithm flow-chart in which can be seen the mechanisms described here.
The parts of the image that are simpler to detect will be identified and eliminated with low exigency so that the remaining items shall be properly gathered into significant similarity classes.
In this preliminary study the algorithm was applied to the 3 images corresponding to the 3 slices as a unique image.

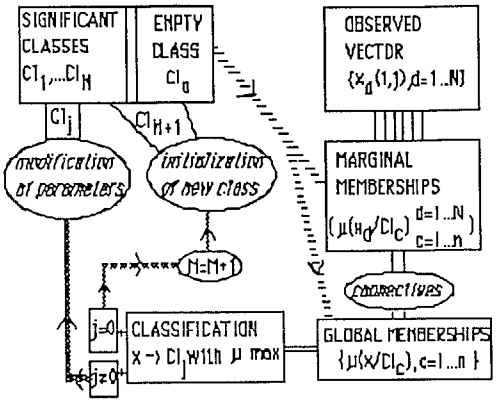
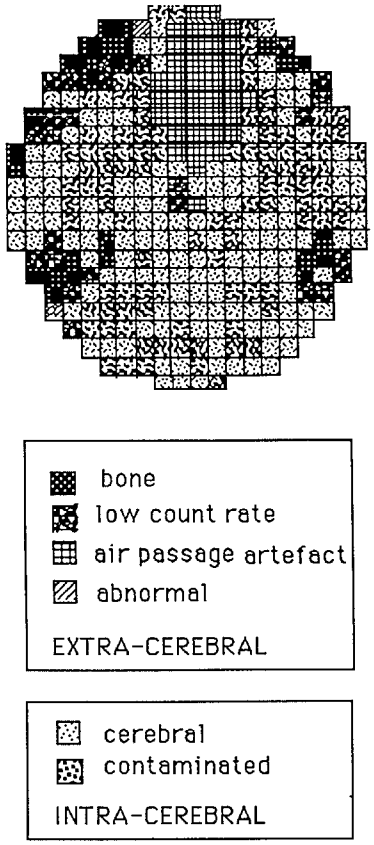


Figure 3

The second extra-cerebral sub-group included classes with lower count-rate, it was located on the edges of the images and in the region of the petrous bone on slice 1. We considered that it consisted in data from the skull. However some pixels pertaining to one or two classes of the second sub-group were located in areas of slices 2 and 3, they obviously belong to the brain. (fig 4). The group of cerebral classes was characterized by its topography and by mid count-rates. Usually, the number of pixels per class was quite large. In addition to these 2 major groups, the LAMDA method provided some classes, the time profile of which differed from the expected dynamics of count-rate (fig 1). These classes included only very few pixels with high count-rate which were usually scattered around air passage artefact. Our study shows that, provided they are applied to well selected groups of pixels, the CBF estimates obtained by the IVM are in good agreement with other methods.The LAMDA method points to the existence of a number of pixels that can be thought as pertaining to the brain but wich should be considered as strongly biased by bone or air passage contamination and thus excluded from calculation.

5 Experimental results.

We studied 16 sets of data obtained in 8 patients, including one normal subject and 7 patients with dementia, Parkison's or cerebral vascular disease. Pharmacological or neuropsychological activations of CBF were performed in some patients. Thus our material included a wide range of CBF values and several patterns of CBF regional distributions. The number of classes provided by LAMDA method depends on the data and on the mixity parameter denoted α in the classification context . With the objective of obtaining about 20 classes, we vary the α values from 0.1 to 0.3 and thus obtained a total number of classes ranging from 15 to 36 according to the exam (table 1). With such a number of classes we found that the number of pixels per class widely varied. We assigned the classes into 2 major groups according to the two following: the sum of the first two values (1st and 2nd minutes) and the ratio of this sum to the sum of the last two values (3rd and 4th minutes). The topography of those 2 groups strongly suggests that they consist of extra-cerebral and cerebral data. The group of extra-cerebral classes could be divided into 2 sub-groups: the first was characterized by high count rate and fast decrease, it was mainly located in slice 1 and its topography was clearly related to air passage artefact. In a few exams, some pixels belonging to this group of classes were located in slice 2. Their topography suggested that these pixels were contaminated by this artefact.



Example of image obtained with LAMDA
Figure 4

REFERENCES

1-*Celsis, Goldman, Heriksen and Lassen 1981.* : A method for calculating regional cerebral blood flow from emission computed tomography of inert gas concentrations.
J. COMPUT. ASSIST. TOMOGR. 1981; 5; pp 641-645.

2-*Banon and Aguilar-Martin 1972* :
Estimation linéaire recurrente de paramètres de processus dynamiques soumis à des perturbations aléatoires.
REVUE DU CETHEDEC 1972; 9, pp 39-86

3-*Chan, Aguilar-Martin, Celsis and Marc-Vergnes 1985* :
Instrumental variable techniques in Cerebral blood flow estimation using very few samples.
in: PROC. IFAC CONF. IDENT. SYSTEMS PARAM. ESTIMATION. pp1219-1222.
Baker and Young (editors), Pergamon Press.

4-*Aguilar-Martin and Piera 1985* :
Les connectifs mixtes: de nouveaux opérateurs d'association des variables dans la classification automatique avec apprentissage.
in: DATA ANALYSIS AND INFORMATICS, IV, pp 253-265
E. Diday et al. (editors), Elsevier Science Publishers B.V. (North Holland)