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Clustering algorithms as classifiers of blood pressure recordings

L.I. Passoni, J. Fritschy, A. Introzzi, F. Clara
Laboratorio de Bioingeniería, Facultad de Ingeniería,
Universidad Nacional de Mar del Plata,
Juan B. Justo 4302-Mar del Plata-Argentina

Abstract

Pattern recognition techniques, such as clustering algorithms, are applied to recordings of arterial distension waveforms to detect emergent properties of data. The feature extraction stage is based on the Fast Fourier Transform components analysis. Statistical K-means clustering helps in the feature selection step. To generalize the method uses both neural network self-organizing feature mapping and neural network supervised learning to classify waves according to patient age. This process shows encouraging results for a set of blood pressure recordings belonging to three differents decades.

1. Introduction

Illnesses characterized by a decrease of elasticity of arterial walls, such as atheroclerosis and hypertension, are one of the most important causes of mortality in the western hemisphere. O'Rourke [1] states that atherosclerosis and aging causes important modifications in blood pressure waveshape, enlarging the sistolic portion while the diastolic one dissapears. This kind of diseases has the characteristic of showing no initial symptoms. This is one of the most important reasons to obtain a process that permits its precocius detection.

Vatner [2] found that the arterial distension waveforms exhibit a similar shape as those of blood pressure. The records are obtained using a bloodles method designed by Introzzi [3]. It uses an instrument to register the arterial distension waveform during cardiacal cycle. It consists of a capacitive transducer attached to a bandage wrist applied to the palpation zone of the radial pulse. An ECG is used to sinchronize data adquisition. The variations of capacity due to arterial pressure are converted into voltage changes, digitalized and stored in a computer system.

These measurements belong to a group of normotensives volunteers, covering different decades. Great differences in waveshape between ages over sixty and below thirty have been observed. The alteration is due to loss of elasticity of the arterial wall [1].The proposed clustering method classifies the records according to normal age patterns, detecting the probable existance of arterial illness if the age of the patient does not agree with the label of the class.

2. METHOD AND MATERIALS

2.1 CLASSIFIER DESCRIPTION

In pattern classification the requirement is to classify the signal set into a finite number of classes (patterns), such that the average probability of misclassification is minimized.

A nonparametric approach based on the self-organizing feature map is prefered, rather than the parametric Bayesian criteria, which assumes a Gaussian distribution.To achieve the best result for pattern classification the use of a feature map is accompanied by a supervised learning algorithm.

A system representation is illustrated in Figure 1, which is briefly summarized here and detailed in the following pages. The first step in the process is the computation of the power spectra of the discrete arterial distensions waves.The feature selection step is performed using a statistical approach (K-medias). During the training mode the spectra of class examples are clustered.Then a supervised learning algorithm is implemented to achieve a better separation between classes. At this point the neural network is trained to recognize the records, producing a set of trained weights. During consultation, unknown records are fed to the neural network and placed into the corresponding class according to similarities computed by the network.

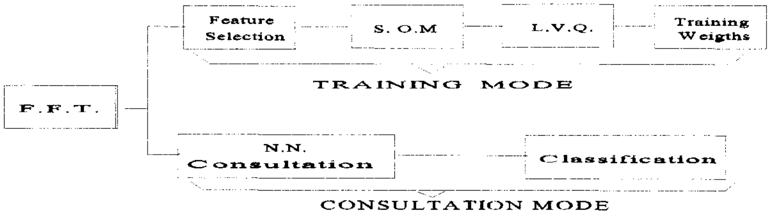

Figure 1:Classifier diagram.

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2.2 FEATURE SELECTION:

One of the most important items to consider in the pattern recognition process is the selection of the attributes that represent the input data [4]. The records of the digitalized signals are transformed using the Fast Fourier Transform of N points, where N depends on the period of the wave in each case.

$$X_k = \sum_{n=0}^{N-1} x_{(n)} W_N^{kn}$$

where :

$$W_N = e^{-j(2\pi)/N}$$

and N= length of the period

The next step is the choice of the spectra components which better contribute to distinguish between classes.

Cluster analysis is a multivariate procedure that detects natural groupings in data. Data are classified into groups, according to their similarity.The K-medias algorithm, as a cluster analysis tool, is used to select the set of frequency components to train the neural network.This method splits a set of cases, not in a hierarchical way, but into a selected number of groups by maximizing between cluster variation relative to within-cluster variation.

A selected group of transformed records that represent in a strong way three different classes, is presented as the set to cluster.

Experiments were made defining always three clusters and different number of frequency components in each trial.

According to the results obtained it was observed that the group of frequency components that provides the best clustering are the first five harmonics, considering their magnitud and phase attributes as a vector of ten components.

2.3 SELF ORGANIZING MAPS

The self-organizing systems are considered a special class of artificial neural network and are referred as self-organizing feature maps. They are based on competitive learning; the output cells of the network compete in their activities by means of mutual lateral interactions, with the result that one neuron is on at any one time.

Those cells that win the competition are called winner-takes-all neurons.

In the Kohonen [5],[6] self-organizing feature map, the neurons placed at the nodes of a lattice become tuned to the input patterns in the course of a competitive learning process. The locations of the neurons (winning cells) tend to become ordered with respect to each other, building a topographic map of the input patterns in which the spatial location of the cells in the lattice correspond to intrinsec features of the input vectors.

The learning process accomplished at the feature map is similar to those encountered in the brain and this is one of the most important justification for calling these maps "neural networks". The cerebral cortex is organized in specific areas, identified by the type of neurons within, like the motor, somatosensory, visual and auditory regions. These cortical maps, where sensory inputs are mapped onto corresponding areas are organized spatially.

The artificial model introduced by Kohonen tries to capture the essential features of computational maps in the brain, belonging to the class of vector coding algorithms.

The most important effects that lead to spatially organized maps are:

a) spatial concentration of the neuron (and its neighboorhood) that best match the input pattern.

b) tuning of the best matching cell and its topological neighboorhood to the present input.

Let x be the input vector, connected in parallel to all the cells i of the network lattice. The weight vector of cell i shall be denoted by wi.
The matching criterion uses the Euclidean distance between x and wi. The minimun distance defines the "winner cell" wc:

$$\|x-w_c\| = \min_i \|x-w_i\|$$

The activity of each neuron is not independent of its neighboorhood; the lattice supports two types of connections:

a) forward connections coming from the input pattern.
b) internal connections due to self-feedback and lateral fedback.

These two types of connections have different aims: the first produces a selective response to a certain input feature and the second produces excitatory or inhibitory effects.

So far a topological neighborhood is defined as Nc, where lateral interaction is enforced. At each learning step, the neurons inside are updated, whereas those outside are left intact. This neighborhood has its centre in the winning cell. Its radius is time-variable and at the beginning, when coarse spatial resolution takes place, it is very wide and is reduced monotonicallly with time.

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The updating process may read:

$$w_i(t+1) = w_i(t) + \alpha(t)[x(t) - w_i(t)]$$

if

$$i \in N_c(t)$$

$$w_i(t+1) = w_i(t)$$

if

$$i \notin N_c(t)$$

where

$$\alpha(t)$$

is the corresponding value of the learning parameter time dependent.

The effect of the above equation is to move the synaptic weight of the winning cell towards the input vector x. After sufficient iterations of the training data, the lattice weights tend to follow the distributions of the input patterns due to the neighborhood updating. The principal steps of the unsupervised training mode are the following:
1.-A synaptic matrix is initilizated with random weigths.
2.-A sample is drawn from the input pattern.
3.-The Euclidean distance matching is calculated.
4.-Matrix weigths are updated.
5.-Iterations of steps 2 to 4 until no noticeable changes in the feaure maps are observed.

2.4 Learning Vector Quantization algorithm

The Self Organizing Feature Map described above acts as a preprocessor in the pattern classification problem. To improve the quality of the classifier decision regions an algorithm of Learning Vector Quantization is used.

The L.V.Q algorithm is a fine tuning method of the class regions. A set of vectors placed in the map are selected to represent their respective classes and they are called "codebook vectors". Several "codebook" vectors are selected to represent each class, helping the decision borders process between classes. The classification of the input vectors ***xi*** is done labelling them with the symbol of the closest codebook vector ***wi***. The initial values of the ***wi*** are set by the trained matrix obtained with the Self-Organizing Feature Method.To determine the label of the codebook vectors a set of input patterns with known classification is presented and the ***wi*** cells are assigned to different classes according with the nearest-neighbor comparison .

Let ***wc*** be the codebook vector closest to ***x*** in the Euclidean metric which label is known. Applying a set of training input vectors, updating ***wc*** as follows:

$$w_c(t+1)=w_c(t)+\beta(t)[x(t)-w_c(t)]$$

if ***x*** is classified correctly,

$$w_c(t+1)=w_c(t)-\beta(t)[x(t)-w_c(t)]$$

if its classification is incorrect,

$$w_i(t+1)= w_i(t)$$

for

$$i\neq c$$

The function

$$\beta(t)$$

decreases linearly with time, beginning with a very small value.

3. RESULTS

For codebook generation, a 12 x 12 ten dimensional S.O.M. matrix is adopted and signals from fifty four different arterial distension recordings are used during the training mode.

The input patterns were random sampled to train the synaptic matrix.

The learning function used was:

$$\alpha(t)= 0.5*e^{(-0.000279*t)} \qquad (3.1)$$

The neigboorhood was of hexagonal type and its radius shrinks linearly, beggining with fifty two cells.

The L.V.Q. process uses seventeen input vectors of known classification and an

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exponential learning function too. These patterns were presented in a sequential way to readjust the neurons weigths.

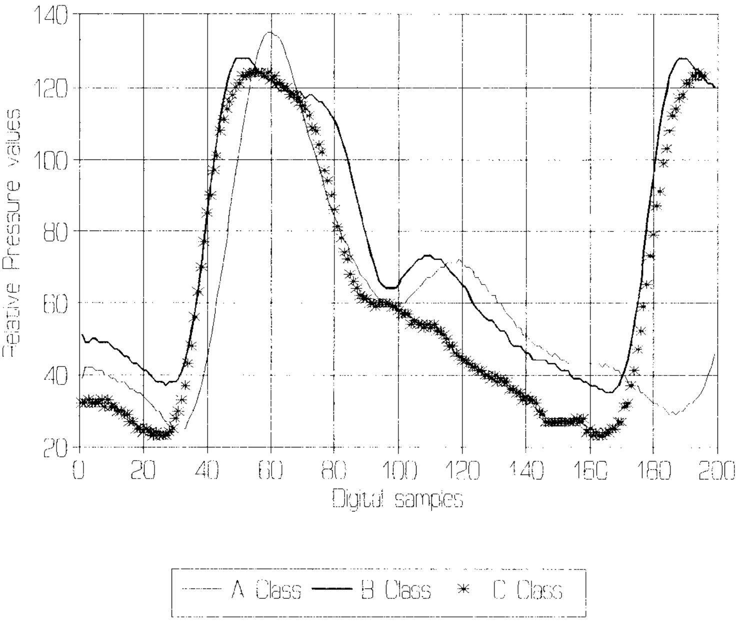

Figure 2: Class representative recordings.

Figure 2 shows characterstics recordings for different classes: class A belongs to the third decade, class B to the fifth decade and class C to the seventh decade.

The labeled cells obtained with the Self Organizing Feature Map are shown in figure 3.
The exponential learning function (Eq. 3.1) showed, among others the best performance. The final state is reached after sixteen thousands iterations.
The marked cells correspond to the codebook vectors, selected as class representative.

								B			
		A				B					
								B			
	A		A		B		$\boxed{B}$				C
									C		
A		A			B						
			A			B		C			C
	$\boxed{A}$										
				B					$\boxed{C}$		
	A					C					C
								C			

Figure 3. Trained matrix after S.O.F.M algorithm.

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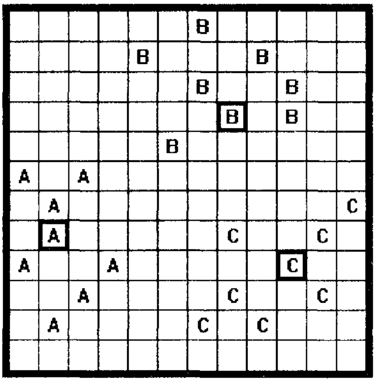

Figure 4.:Final mapping after L.V.Q. algorithm .

The L.V.Q. algorithm results are shown if Figure 4.

The codebook vectors attract the other members of their class, improving the quality of the decision borders and creating well-defined regions.

Table 1displays the results obtained during the consulting mode.

The trials were performed with a set of recorded signals outside the training set.

4. CONCLUSIONS

	A	B	C	Missed
A	27/30 90%			3/30 10%
B		24/30 80%		6/30 20%
C			26/30 87%	4/30 13%

The decade representative signal quantization of the arterial distension recordings was developed using S.O.M (algorithm unsupervised learning method), for computing the codebook vectors.

The L.V.Q. (supervised learning technique), finally provides good performance for pressure waves classification.

Table 1: Summary of test results.

5.BIBLIOGRAPHY

1. O'Rourke M. The arterial pulse in health and disease. *American Heart J.* 82: 687-702, 1971.

2. Vatner S., Pasipoularides A.,Mirsky I. Measurements .Measurements of arterial pressure-dimension relationships in conscious animals. *Ann. Biomed. Eng.* 12: 521-34, 1984

3. Introzzi A., Clara F., Valiente S.M. Sistema de registro de ondas de dilatación arterial.
VI Congreso Argentino de Bioingeniería. Tomo de resúmenes pp9, 1988.

4. Devijver R., Kitter J. *Pattern recognition: a statistical approach.* Prentice Hall. 1982.

5. Kohonen T., The self organizing map. *Proceedings of IEEE* 78, 1464-1480.

6. Kohonen T., Physiological interpretation of the self-organizing map algorithm. *Neural Networks* 6, 895-905.

7. Haykin, S. *Neural Networks.* MacMillan 1994.