MIXED ACOUSTIC EVENTS CLASSIFICATION USING ICA AND SUBSPACE CLASSIFIER

Georges Linares, Pascal Nocera, Henri Meloni

C.E.R.I. 339 Chemin des Meinajaries
BP 1228-84911 Avignon Cedex 9
France
e-mail: linares,nocera,meloni@univ-avignon.fr

ABSTRACT
This paper describes a new neural architecture for unsupervised learning of a classification of mixed transient signals. This method is based on neural techniques for blind separation of sources and subspace methods. The feed-forward neural network dynamically builds and refreshes an acoustic events classification by detecting novelities, creating and deleting classes. A self-organization process achieves a class prototype rotation in order to minimise the statistical dependence of class activities. Simulated multidimensional signals and mixed acoustic signals in real noisy environment have been used to test our model. The results on classification and detection model properties are encouraging, in spite of structured sound bad modeling.

1. INTRODUCTION
Contrary to what happens in laboratory conditions, acoustic signal acquisition in real situations may be achieved in noisy and varying environments. Noise modeling by supervised learning assumes noise predictability. Unfortunately, it is difficult to obtain a sufficient description of all sounds able to disrupt an acoustic information processing system, because of large noise and context variability. Therefore, low a priori knowledge based techniques provide interesting solutions to this noise unpredictability in complex environments. That is one of the reason why there has been a growing interest in unsupervised learning rules over the past years, especially noticeable in linear and nonlinear hebbian learning rules for blind separation of sources [1] [2] [3] [4] [5].
In this paper, we propose a new neural architecture for mixed acoustic events classification inspired by neural methods for source separation and Subspace Classifier [6] [7].

2. PRINCIPLE

We use a feed-forward neural network for acoustic events detection and classification. Each output cell is associated with an event class, and several output cell activities are considered as simultaneous presence of events of different classes. The unsupervised neural classifier self-organizes in order to adapt itself to environment evolutions. This self organizing process is made on line, by detecting novelities, creating and

![Figure 1: Principle of neural processing and adaptation to input signals](image-url)
deleting classes. This first data space modeling reduces input space dimension to a smaller one. A second process computes a decorrelation matrix which achieves prototype rotations in order to minimise the second order moments of the network output. Decorrelation operator application on network outputs is equivalent to a class prototype rotation. So, the computed operator is applied directly to prototype matrix, and the system stabilizes itself in a state of uncorrelated output cell activities. The figure 1 shows successives process applied.

3. ARCHITECTURE

The neural net has two fully inter-connected layers. The input layer receives the coefficients of stimuli vectors. The output layer has one cell per class, and another for novelty.

![Figure 2: Architecture of neural network](image)

Each class is represented by a prototype \( P_i(t) \), an instantaneous activity and an inertia \( I_i(t) \). Inertia is computed from the temporal signal of the cell activity by a classical alpha-beta filter:

\[
I_i(t + dt) = \beta |act_i(t)| + (1 - \beta)I_i(t)
\]

The choice of the parameter \( \beta \) determines the persistence of network memory.

Cell activities are computed by the projection of stimuli vectors on prototype space. It is assumed that class prototypes are linearly independent, that is implicitly respected in the new class acquisition stage. The output vector \( A_t \) is computed at time \( t \) by

\[
A_t = P^+(t)V_t
\]

where \( V(t) \) is the stimulus vector, \( P \) the prototype matrix (each column of \( P \) is a prototype vector), and \( P^+ \) the pseudoinverse of \( P \).

Consequently, the weight matrix is the pseudoinverse of the prototype matrix.

\[
W_t = P^+(t)
\]

The novelty cell activity is computed by:

\[
act_n(t) = \frac{||V(t) - V_n(t)||}{||V_n||}
\]

where \( V_n(t) \) is the component of \( V(t) \) inside the prototype space. We do not consider several simultaneous class activations as a competition between classes, with a winner. We rather consider several significant output cell responses as the simultaneous presence of different event classes. This is possible only if the linear mixture of "physical" events corresponds to the same linear combination of input vectors. For acoustic applications, only the additive noise will be correctly modeled and separated from the useful signal. Therefore, in such an acoustic context, linear transformation will be used for converting one-dimensional signal into input acoustic vectors sequence, such as FFT in sliding temporal windows.

4. DYNAMIC CLASSIFICATION LEARNING

The system is initially empty, therefore there are no known classes. A new class is created when novelty cell activation exceeds a fixed vigilance threshold, with the input vector as the new class prototype. The latter is necessarily linearly independent from the current prototype base, because the novelty cell represents a distance between prototype subspace and input vector. This distance is computed from the input vector component which is orthogonal to the prototype space. Low inertia means low class representativeness. So the system permanently scans class inertias. If one of them is lower than a deletion threshold, then the class will be killed.

This class integration and deletion on-line process induces a stabilisation of subspace dimension, which depends on the thresholds and the input variability. This stabilisation is necessary, because the system sensitivity depends from number of class known.

5. PROTOTYPE EVOLUTIONS

In this class acquisition method, the first input vector is always in the prototype base. In complex environments, the presence of several events at system initialisation is likely. In this case, the new prototype is a mixture of different potential prototype classes. In such a situation, using only the above described learning process may lead to bad classification. Here is an example of a catastrophic scenario: A,B,C,D are acoustic events, V(t) stimuli vector at
The application of the uncorrelation operator $C^{-1}$ to classifier outputs is equivalent to a prototype rotation:

$$S(t) = C^{-1}_i W_i^+ V(t) = (W_i C_i)^+ V(t)$$

Thus, the operator is applied directly to the prototype matrix.

## 6. Experiments

In the first test, the first seven alphabet pattern letters have been randomly mixed. 2000 samples of pattern mixtures have been used as input, without any information concerning original shapes and pattern number. Seven classes have been effectively found, and original patterns were recovered with low noise level (figure 3).

The proof of this algorithm convergence, and more information about it can be found in [4]. This algorithm can only be used for non-stationary signals separation, and input signals must have zero means and unity variances. Therefore, cell activities are normalised in order to respect these constraints. The non-stationary input signals constraint may not to be respected in the case of stationary class activities. Therefore, we have added a sigmoidal term to the original learning rule, which allows to regularise learning dynamics in locally silent areas. The learning rule used is:

$$\frac{dC}{dt} = F_i (I + C^T)^{-1} \text{diag} \left< s(t), s(t)^T \right>^{-1} < s(t) s(t)^T > -1$$

with $F_{i,i} = \frac{1}{1 + \epsilon} \frac{\|y(t)\|}{\|y(t)\|}$, $F_{i,j} = 0$ if $i \neq j$.

The second test (figure 4) shows a signal in a real subaquatic environment, and system responses. The first line is the signal spectrogram obtained by a FFT computed in a sliding temporal window. There is a vector of 256 coefficients for each 10 ms. The second line shows the novelty cell activity. New classes are detected from the local maximums of that curve. The third line represents the prototype space dimension relatively to the input space dimension. The other lines show most meaningful class activities.

Recurrent events have been well detected. Their first occurrence set off high novelty cell response, and other occurrences of class 3 and class 4 events have been well classified. At time 350, a class 3 event and a class 4


---

**Figure 3:** Detection and classification of multi-dimensional simulated events

**Figure 4:** Detection and classification of multi-dimensional simulated events
event have been occurred simultaneously, and the system have detected correctly the two events. The fifth class has been created from the first (and only) isolated event occurrence. The last isolated event has occurred a time 400. It is a noise which have large temporal structure. These temporal evolutions in large frequency domain have produced several classes creation. It has been badly modeled. That illustrates bad time representation in our model.

7. CONCLUSION AND FUTURE PROSPECTS

The first results concerning model properties for classification and novelty detection seem to be encouraging, in spite of the structured sound bad modeling. Using other source separation techniques based on high order statistics could improve the system's performances. We are currently working in grouping low level class in meta-classes encoding temporally correlated acoustic events.

8. REFERENCES


Figure 4: Detection and classification of acoustic events