ESANN'1996 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-25-26 April 1996, D-Facto public., ISBN 2-9600049-6-5, pp. 309-314

Fast Signal Recognition and Detection using ART1 Neural Networks and Nonlinear Preprocessing Units based on Time Delay Embeddings

R. Dogaru, A.T. Murgan, C. Comaniciu
"Politehnica" University of Bucharest,
Applied Electronics Department,
Str. Turnu Magurele Nr.7, Bl. C1A,
Apt. 100, Sector 4, Bucharest, ROMANIA,
Email: radu_d@vala.elia.pub.ro

Abstract: A new method for fast adaptive signal recognition and detection using neural networks is proposed. The method is essentially based on converting samples from the signals to be detected or classified into a binary "character-like" matrix which can be then used to train fast adaptive neural networks. While this preprocessing method may be applied to any neural architecture designed for character classification tasks, we have used to test the performances on modified ART1 networks. These networks were chosen due to their fast learning capabilities making them very attractive for on-line signal classification tasks. The preprocessing method was much inspired from the embeddology theory which gives appropriate tools for nonlinear systems identification, based only on observing a time-sequence generated by the underlying nonlinear system. Experimental results proved that efficient and fast decisions can be done for signals coming from sources which can be modeled as nonlinear dynamic systems.

1. Introduction

Neural Networks proved to be efficient in different signal processing problems especially due to their adaptive nature [7]. Dealing with signals as particular cases of information patterns, one must choose appropriate methods for extracting the effective information from a set of given samples representing the signal. These methods, often called preprocessing schemes are needed as interfaces between the signal sequence and neural-network input. They may dramatically improve the overall system performances by extracting only the essential information from signal. As a basic requirement for any preprocessing scheme is that they must preserve the essential features of the original time sequence taken during an observation window.

For signal classification or detection tasks different preprocessing methods were reported in literature, most of them being based on using linear time-frequency transforms such as the Short-time Fast Fourier transform (SFFT) [3]. Many speech recognition systems make use of this family of transforms [7]. Principal Component Analysis is also a very useful preprocessing methods especially when using high-

ESANN'1996 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-25-26 April 1996, D-Facto public., ISBN 2-9600049-6-5, pp. 309-314

dimensional data patterns. Particular neural networks were developed to perform (linear and non-linear) PCA [8] . Other preprocessing methods are based on tape-delayed lines, some of them being also included in the synapse model of the feed-forward networks. This idea was successfully exploited for signal prediction or speech recognition. What is common to all these methods is that they gives continuos-valued patterns and thus the neural network must be designed in order to process such kind of patterns. It is however well known that particular neural networks such as BAM [7] or ART1 [4] which can accept only binary patterns, are very fast in both learning and retrieval comparing with most of the neural network models which can process continuos-valued patterns. These networks are also easily to be implemented in VLSI technologies. On the other hand, recent studies [1] [9] suggests that many signals may be considered as being produced by nonlinear processes and thus it is more naturally to think about preprocessing schemes which may extract the essence of the nonlinear mapping which gives a particular signal sequence. In [2], these suggestions were exploited for signal detection by using a specially designed feed-forward network which learns to classify two-dimensional phase-plane patterns. Good performances were reported (-9dB SNR signal detection with 8% error) but the system is not capable to work on-line due to the large times needed to train the feed-forward net. Instead of these, the method proposed in this paper allow to get "character-like" binary feature vectors from a time-delay embedding obtained from a sliding rectangular window which covers the last "w" samples of the incoming signal. Using ART1 neural networks, "on-line" clustering may be easily achieved allowing to use this preprocessing method in real-time systems. While the preprocessing algorithm is O(w), the computational complexity of the overall system is minimized allowing also an efficient hardware implementation. Some properties of the proposed preprocessing method were exploited to efficiently remove noise from the time-delay embedding, simulation results proving fast recognition capabilities even in the presence of severe noise.

2. The architecture and principle of the recognizing system

In Fig. 1. the block diagram of the overall system is presented. The task may be a detection one (if a noisily signal must be correctly assigned to a particular output class) or simply a recognition one. The system is composed by 1) the preprocessing scheme, 2)the neural network recognition block, and 3)the majority vote decision network

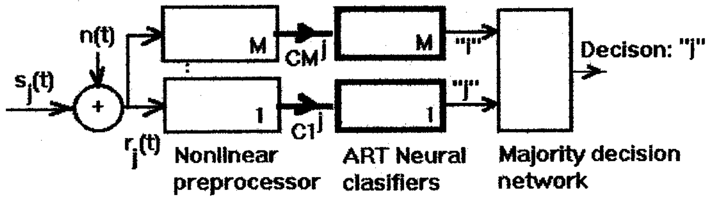


Fig.1. Architecture of the recognizing system

ESANN'1996 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-25-26 April 1996, D-Facto public., ISBN 2-9600049-6-5, pp. 309-314

The ***preprocessing scheme*** acts over a fixed length sliding window containing w samples of the signal. We assumed that on short time intervals, signals may be considered as being generated by nonlinear dynamical systems. Thus, signal non-stationarities are considered as changes in the nonlinear model of the signal source. For stationary signals the model must remain unchanged. The state dynamics the associated source systems may be approximately reconstructed according with the theory of embeddings [10] by a ***time-delay embedding.*** This can be achieved by using the sliding window sequence of samples {x(t)} from the input signal.
A reconstructed state vector $X = [x(t), x(t-1\cdot\tau), .. x(t-Q\cdot\tau)]$ is thus obtained for each time moment, where Q+1 is the dimension of the reconstructed space. In order to obtain "character-like" binary patterns, our preprocessing method is based on two-dimensional time-delay embeddings (Q=1) often called ***phase space*** representations.

While the data needed for training the neural networks must be in binary form, a discrete phase space (DPS) representation is needed. First, a continuos phase space (CPS) representation is computed for each observation window as a set of pixels, each of them being characterized by the coordinates:

$$\{(px, py)_t\} = \{(x(t), x(t-\tau))\}_{t=\overline{t0,..t0+w-1}}$$

Two pixels corresponding with consecutive time moments are joined with a line in the CPS. Then, using interpolation and quantization a binary *res*res* matrix $\{C_{i,j}\}_{i=1,..res;\,j=1,..res}$ is generated from the CPS. This matrix (the DPS) is the output of the time-delayed embedding preprocessor (TDEP) and here the lines between two adjacent pixels were replaced with "1" pixels and the position of each pixel in the CPS was quantified in order to be represented as an integer within the domain [0,res-1]. All other pixels are "0" ones. These binary matrices fed the neural network classifier. The shapes of these character-like patterns are strongly related with the corresponding signals but they depends also on the preprocessing scheme parameters. An important feature of this transform is related with the capability of removing stochastic signals by simply replacing each sample $x(t)$ with a linear filtered version $x'(t) = \sum_i x(t-i)\cdot w_i$. While the shape of the DPS given by the deterministic component of the signal remains almost unchanged, the shape given by some stochastic component (e.g. white noise) is dramatically affected, the result being a character pattern almost like the one obtained for the unperturbed signal (Fig. 3c).

Figure 2 shows character-like patterns for different signals. In Figures 2.a, 2.b and 2.c patterns obtained from periodic (α=2, α=3), and aperiodic signals ($\alpha = \sqrt{2}$) are presented (the dynamics is given by eq.1):

$$y_n = \sin(n/10) + \sin(\alpha \cdot n/10). \qquad (1)$$

Figure 2.d represents a pattern obtained from a chaotic signal (eq. 2)

ESANN'1996 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-25-26 April 1996, D-Facto public., ISBN 2-9600049-6-5, pp. 309-314

$$y_0 = 0.3 \quad y_1 = 0.4 \quad y_2 = 0.73$$

$$y_{n+1} = 5\frac{y_n}{1+y_n^2} - 0.51y_n - 0.7y_{n-1} + 0.5y_{n-2} \tag{2}$$

Figures 2.e and 2.f. represent patterns obtained from real vocal signals (phonemes "a" and "u").

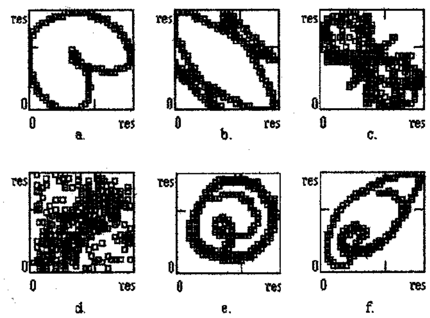


Fig. 2. Character-like patterns obtained at the output of preprocessor (res=32):
a. periodical signal $\alpha = 2$; b. periodical signal $\alpha = 3$; c. aperiodical signal $\alpha = \sqrt{2}$; d. chaotic signal; e. vocal signal "a"; f. vocal signal "u".

In order to exploit the binary character of the preprocessed patterns the ART1 neural network [4] was chosen for the classification task especially due to its fast speed learning and low computational complexity. According to [4], the vigilance parameter could be modified during the learning process being dependent of the application (it can be chosen larger when the network learns, and smaller during the recognition step). In the ART1 model, the learning processes continuously modify the prototype for each class and we observed increasing misclassification rates especially for nonstationary signals. Thus, a modified ART1 algorithm was proposed instead the classic one

. The modified ART1 algorithm consists of two separate learning and retrieval phases; During the first phase, the prototype assigned to each class is learned. In the second phase, the ART 1 algorithm is reduced to a classifying system., the learning being locked These modifications allow to avoid the saturation phenomena of the ART 1 systems, all misclassifications (except confusion between classes) being assigned to a "garbage" class.

The majority vote decision network was introduced in order to improve the misclassification rates for both detection and recognition tasks. The input signal is divided in a number of observations sequences. Each sequence is separately processed and the decision classes for all M classifiers are used in order to infer a final decision.

ESANN'1996 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-25-26 April 1996, D-Facto public., ISBN 2-9600049-6-5, pp. 309-314

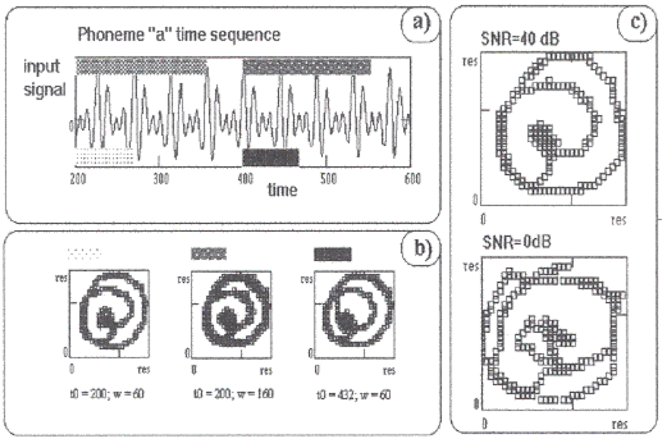
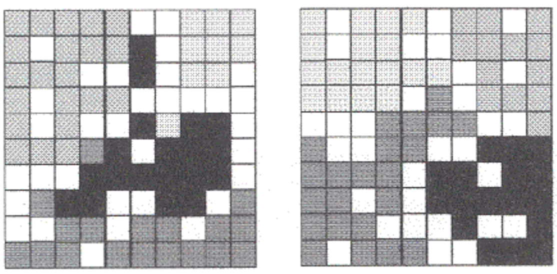


Fig. 3. TDEP patterns: a) The input time-sequence (without noise); b) Different TDEP patterns obtained from this sequence; c) Patterns obtained from the white-noise perturbed sequence using the filtered version of TDEP .

3. Simulation results

In order to test the performances of the proposed preprocessing scheme a Kohonen SOM network [6] was trained with patterns obtained from the same signals (four different phonemes with noise) using FFT-based preprocessing and the scheme proposed above.



a) b)

Fig. 4. Effects of the preprocessing scheme to the distribution in Kohonen maps; a) FFT-based preprocessing b) Time-delay embedding preprocessing . Each gray level is assigned to a particular class

After calibration, the SOM-network was used to recognize test patterns from the same four classes. The misclassifications rate was better for the new method especially for high perturbed signals (SNR<10dB), and the class separation on the Kohonen map was also improved (see. Fig. 4). Notice that in the FFT case, each input pattern was a 64 dimensional vector while in the case of the nonlinear preprocessing 8x8 binary matrices were used as patterns. In order to test the performances using ART1 classifiers four classes of signals altered by white noise

ESANN'1996 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-25-26 April 1996, D-Facto public., ISBN 2-9600049-6-5, pp. 309-314

corresponding to Fig.2a, b, d, and e were considered. Using appropriate vigilance parameter low misclassifications rates (<5%) were achieved even for SNR=-10dB while the computation time in the learning phase was hundred times smaller than using the Kohonen network.

4. Conclusions

A new preprocessing method was proposed in order to exploit the fast learning and retrieval capabilities of ART1 neural networks for signal processing. Based on embedding theory the proposed method allow fast feature extraction in form of character-like patterns that can be further processed using any type of neural classifier. Simulation proved higher immunity to noise than other linear preprocessing methods at a better effective information compression rate. A system using this preprocessing method and the ART1 networks was described, simulations proving high performances for signal detection and classification in noisy environments. High speed and reduced computational requirements make this solution very attractive for parallel VLSI implementation. While the system was tested under the assumption that signals are generated by nonlinear dynamical systems further research will be directed to investigate the effects of different classes of signals on the overall performance of the proposed system.

References

1. M. Banbrook, S. McLaughlin, “Speech characterization by nonlinear methods”, in Proceedings of the 1995 IEEE Workshop on Nonlinear Signal and Image Processing, Ed. I. Pitas, pp. 396-398
2. D.L. Birx, S.J. Pipenberg, “Chaotic oscillators and complex mapping feed forward networks (CMFFNS) for signal detection in noisy environments”.
3. R.E.Blahut, “Fast Algorithms for Digital Signal Processing”, Addison-Wesley Publishing Company, 1988.
4. G.A. Carpenter, S. Grossberg, " The ART of Adaptive Pattern Recognition by Self-Organizing Neural Network", IEEE Computer, Vol. 21, 1988, pp. 77-88.
5. A.M. Fraser, "Information and Entropy in strange Attractors", IEEE Trans. on Information Theory, Vol 35, No. 2, March 1989, pp. 245-262.
6. Kohonen, T, “The self-organizing map “, Proceedings of the IEEE, 78, pp. 1464-1480.
7. B. Kosko, "Neural Networks for Signal Processing", Prentice-Hall, 1992.
8. Kung, S.Y. and C. Diamantras, “Neural networks for extracting unsymmetrical principal components”, 1’st IEEE Workshop on Neural Networks for Signal Processing, 1991, pp. 50-59.
9. S. McLaughlin and A. Lowry, “Nonlinear dynamical systems concepts in speech analysis”, in EUROSPEECH’93, pp. 377-380, 1993.
10. F. Takens, “Dynamical Systems and Turbulence”, vol. 898 of Lectures in Mathematics, pp. 366-381, Berlin, Springer 1981.