ART 2-A ON T-NODE MACHINE APPLICATION TO AUTOMATIC CLASSIFICATION OF ALL-NIGHT SLEEP STAGES

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Abstract

This article presents the parallelization on parallel computer of training sequences of ART 2-A neural network. It is applied to the automation of the classification of human sleep stages. We show that the computation time is reduced by a speed-up factor of 10. The results obtained were 92% of correct classification on the training set and 75.5% on the testing set.

Keywords : parallelism, neural networks, pattern recognition, ART.

I INTRODUCTION

The study of human sleep consists in monitoring different physiological activities simultaneously and continuously during the night. The modifications of these signals during the night define 6 states of vigilance described in a standard manual [1]. Each sleep stage, characterised by specific shapes of the polygraph curve, is visually labelled by an expert over 30-second periods during the whole night. Automation of the sleep analysis was necessary because of the amount of information to be analysed (about 1000 30-second pages per night). An automatic sleep analysis system was processed on the basis of an ART 2-A neural network applied to parameters extracted from digitised signals. These parameters are estimated on a 30-second page [2]. A set of 12 complete nights (12455 pages) established by experts served for the training set and independent 11-night set (11745 pages) for the testing set. An inter-expert analysis gave 88% agreement on the quotation of the same night of sleep.

II THE ART-2A NEURAL NETWORK

Adaptive Resonance Theory (ART) neural networks were introduced by Carpenter and Grossberg [3]. These neural models can estimate a decision function thanks to "prototype" calculation elements. A prototype is a vector associated to a class. For the application considered, we used a variation of this network called ART-2A [4].

III THE COMPUTER SYSTEM

We have used an Unix workstation linked by an interface to a M.I.M.D. T-NODE computer. The T-NODE computer is a high performance parallel computer based on a reconfigurable T800 transputer network. Each transputer of the T-NODE has a local memory of 4 Megabytes. We have configured this system in a pipeline architecture. The first processor of this pipeline is called master and the others are called slaves.

IV PARALLELIZATION OF ART-2A

The parallelization method is the following:
First of all, a simulation table to be tested is constituted with different networks configurations parameters.
The Master processor performs the following tasks:
- In the initialisation phase, it numbers all processors from *1* to *p* in order to identify them. It reads the training set and testing set and it sends these two data-bases to the *p* processors available of the T-NODE.
- In the computation phase, it sends the parameters of ART-2A contained in the simulation table. Each network configuration is processed by one and only one processor among the *p* processors. This allocation is performed by a process running on the master processor which knows the state of each processor (busy or free). The parameters contained in the table are then broadcasted to the free processors.

The slaves processors perform the following tasks :
1) In the initialisation phase, they wait to be labelled and to receive the training set and testing set.
2) In the computation phase, each T-NODE processor tunes an ART-2A network according to the specific set of parameter allocated. The results obtained are sent to the master processor which collects the results. These results are the performances obtained on training set and testing set and the number of prototypes found. The slave processor is then desallocated. If needed, the master processor can then allocate a new configuration parameters.

V PERFORMANCE AND RESULTS OF THE SIMULATIONS

The results of the parallel implementation of the simulations of ART 2-A on the T-NODE are summarised in figure 1. We have launched 32 simulations (or network configuration). Each one corresponding to a specific value of ART threshold [4].

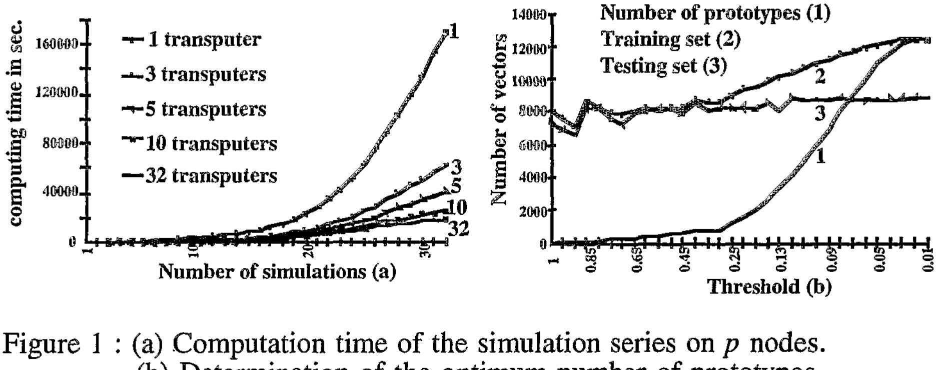

Figure 1 : (a) Computation time of the simulation series on *p* nodes.
(b) Determination of the optimum number of prototypes.

Figure 1 (a) shows the computation time function of the number of processors and of the among of simulations. The computation time of each simulation is different for each threshold. The sequential computation time of this 32 simulations is about 47 hours. The parallel computation time is below as 5 hours. The speed-up factor is 10 and the efficiency 31%.

The upper curve on figure 1 (b) represents the number of well-classified vectors on the training set, the middle curve the number of well-classified vectors on the testing set and the lower curve the number of prototypes as a function of the threshold parameter.
One can see that the probability of correct classification of the training set increases slowly as the number of prototypes increases. On the other hand, for the testing set, one sees a stabilization of classification for a threshold greater than 0.45. The optimum number of prototypes is empirically fixed at 4121 for a threshold of 0.12, which corresponds to the first correct classification maximum on the testing set. The neural network chosen is used on our acquisition system to analyse the sleep nights automatically.
This network needs 0.8 seconds to classify one sleep page. In deferred time, 13 minutes are necessary to classify a sleep recording night (1000 pages).

VI CONCLUSION AND PROSPECTS

The parallel implementation of simulations of the ART 2-A training algorithm of a neural network on T-NODE parallel computer (32 T800) has reduced the computation time of a series of 32 simulations to be tested by a factor of about 10, which represents a gain of 42 hours CPU.
This computer has allowed us to perform the training of the connectionist network on a large-scale data-base to obtain good robustness of the Artificial Neural Network (ANN).
The correct classification percentage obtained is 92% for the training set and 75.5% for the testing set. In the generalisation phase, the classification result approaches the optimum result of 88% of inter-expert agreement computed on the visual analysis of the same sleep night.
The speed-up of the parallelization of simulations opens the way to new parallel simulations in the field of ANN applied to pattern recognition.

VII REFERENCES

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