Learning and Nonlinear Models - Revista da Sociedade Brasileira de Redes Neurais (SBRN), Vol. 4, No. 1, pp. -24-31, 2006

ITERATIVE APPLICATION OF THE aiNET ALGORITHM IN THE CONSTRUCTION OF A RADIAL BASIS FUNCTION NEURAL NETWORK

SANDRO RAUTENBERG[1,3], LUCIANO F. DE MEDEIROS[2,3], WAGNER IGARASHI[3], FERNANDO O. GAUTHIER[3], ROGÉRIO C. BASTOS[3], JOSÉ L. TODESCO[3]

[1]UNICENTRO - Universidade Estadual do Centro-Oeste
[2]Grupo Educacional UNINTER - Curitiba - PR - Brasil
[3]Programa de Pós-Graduação em Engenharia e Gestão do Conhecimento, UFSC
Endereço para Correspondência - Caixa Postal 476 - 88040-900 - Florianópolis - SC - Brasil
E-mail: srautenberg@unicentro.br, lfm@egc.ufsc.br, igarashi@stela.org.br, gauthier@inf.ufsc.br, rogerio@inf.ufsc.br, tite@egc.ufsc.br

Abstract - This paper presents some of the procedures adopted in the construction of a Radial Basis Function Neural Network by iteratively applying the aiNET, an Artificial Immune Systems Algorithm. These procedures have shown to be effective in terms of i) the free determination of centroids inspired by an immune heuristics; and ii) the achievement of appropriate minimal square errors after a number of iterations. Experimental and empirical results are compared aiming at confirming (or not) some hypotheses.

Keywords - Artificial Immune Systems, Radial Basis Function Neural Network, aiNET.

1 Introduction

In the 80s and 90s some studies involving Artificial Intelligence (AI) focused on the creation and use of Hybrid Intelligent Systems. These systems were supported by two or more AI techniques, on the pretext of improving results or overcome limitations of a particular AI technique. Genetic Algorithms (GA), for example, were employed in the specification of initial architectures of Artificial Neural Networks (ANN); Expert Systems (ES) were used as a justification mechanism to ANN answers; Fuzzy Sets were used in the treatment of uncertain reasoning in ES.

Another recent fact that is worth mentioning is the emergence of a new AI technique, named Artificial Immune Systems (AIS). Briefly, AIS are a technique that captures biological aspects of the immune system, implementing inspired metaphors, which can be applied to various areas such as pattern recognition, computer security, robotics, optimization, control, machine learning, data analysis, among others [Silva, 2001]. In this sense, the sort of AIS applications can be compared to ANN ones [Dasgupta, 1997]. On Hybrid Intelligent Systems, studies of the coupling of AIS and ANN are seen in [Silva 2001] and [Feyereisl and Aickelin, 2006].

In respect of ANN, it can be pointed out two crucial issues, which can be seen as complex tasks in the construction of solutions based on this technology. The first point refers to the empiric search involved in the construction task, intended to find the ideal parameters of an ANN topology. The second is the casualty for the weights initial determination (usually random) in the synaptic connections.

Specifically, this paper deals with the construction of Radial Basis Function Neural Network (RBFNN). Although this ANN model may have their weights determined according to the training data, eliminating the coincidence aspect, this process still has some degree of empiricism. Therefore, the search of the optimal number of neurons in the intermediate layer and the distribution of these neurons in a space decision are crucial for the optimal performance of a RBFNN. To overcome this limitation, seeking support from other technologies has a great value.

By coupling two paradigms (i.e. ANN and AIS), this study exposes the iterative employment of Artificial Immune NETwork algorithm (aiNet) in the RBFNN construction. This hybridization form has shown to be viable for two main reasons: i) it removes empiricism from determining the RBFNN topology and ii) it ensures the optimized minimization to an error measure. By comparison , this paper takes the results obtained by Todesco (1995) in a human chromosome classification task. For this, the structure of the article includes, in addition to this section, the theoretical background on the paradigms and the methodology employed in the RBFNN construction. Following, the results and comparisons are presented, as well as the conclusions of this work.

2 Theoretical background

2.1 Radial Basis Function Neural Networks (RBFNN)

RBFNN is defined in the literature as a kind of ANN that has radial activation functions on its intermediary layer. In its simplest form, a RBFNN consists of three layers of neurons (Figure 1). The first layer acts as the input layer of the ANN. The second layer is characterized as a high-scale dimension, which promotes a nonlinear transformation of input space dimension by computing radial functions in their neurons. And the third one, the output layer, outputs the ANN response, promoting a linear transformation of the intermediary layer high-scale dimension to the low-scale dimension [Pandya, 1995].

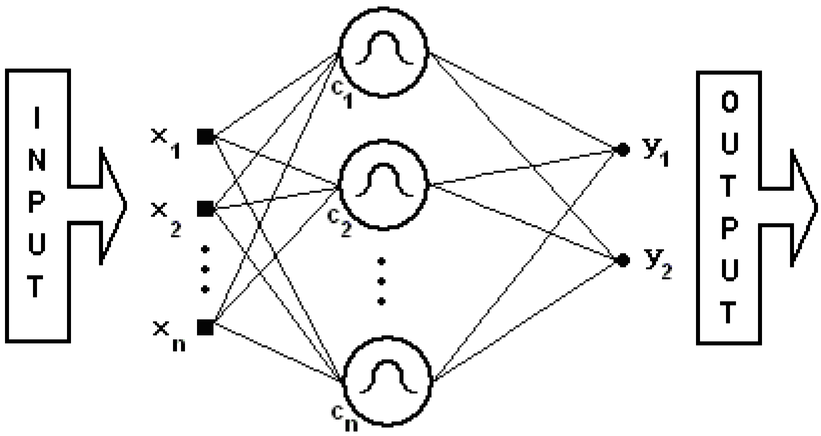

Figure 1: RBFNN graphical representation.

One of the advantages in the RBFNN use is the training speed, taking into account that this process involves, usually, two distinct stages: an unsupervised training and a supervised training. In the unsupervised training the centers are created for the intermediary layer. Commonly, this stage employs k-means algorithm [Todesco, 2006]. In supervised training, a linear method is employed to minimize the established error measure.

However, it is important to note that the RBFNN performance measure is intrinsically linked to the intermediary layer determination. Therefore, the specification of the number and the format of its centers issues empirical addressed to the designer during the implementation of a RBFNN.

To overcome the reported empiricism in this paper we have investigated the application of an Artificial Immune System algorithm, the Artificial Immune NETwork (aiNet), as part of an Intelligent Hybrid System that is responsible for determining the number of centers and its initial positioning on a decision hyperplane. In other words, the aiNet algorithm is used as part of a method to initial determination of the RBFNN intermediary layer. Zuben & Silva (2001) and Diao & Passino (2002) have carried out research following this principle, but not in an iterative way.

2.2 Artificial Immune Systems

To Nasraoui et al. (2003), natural organisms display powerful processing and learning mechanisms, which enable beings to survive and self-proliferate for generations in dynamic environments. In this context, the immune system is an important system of defense that helps in a self-homeostasis (understanding systems as a body), recognizing and removing strange bodies named antigens (e.g. viruses and bacteria).

In this sense, it is understood that the dynamics of an immune system shows signs of cognitive intelligence (recognition of antigens) and learning (maintenance of a community of antibodies), taking into account the fact that these signals are also studied in the AI field. So, recently, the human immune system has been the inspiration source to a new AI technique, named Artificial Immune Artificial Systems (AIS). Historically, according to Zuben & Silva (2006), the AIS precursor work was "The Immune Systems, Adaptation, and Machine Learning" written by Farmer, Packard and Perelson [Farmer et al, 1986].

AIS can be defined as adaptive systems inspired by theoretical immunology, observed immune functions, principles and models, which are applied to problem solving [Timmis, 2004].

As other AI techniques, AIS are based on local computations of processing units (antibodies), as in ANN and artificial neurons or GA and chromosomes. Biologically, AIS take into account a few properties [Dasgupta apud Alves et al, 2004]:

- The immune system can recognize and classify different patterns and produce selective responses. In addition, it uses a combinatory process that generates a set of lymphocyte receptors, with the property of maximizing the chances that at least some lymphocytes recognize a particular antigen.
- The system learns, by experience, the structure of a given antigen. When B cells (in immunology, kind of cells that recognizes antigens) are activated, some of them become memory cells, with an extended life time. These cells help the body to produce a rapid immune response even when an antigen is found in the future. The system automatically determines a balance between economy and performance, maintaining a sufficient number of B cells.
- The immune response mechanism is naturally self-regulated. There is not a main control over the immunologic system that governs it. The immune response's regulation can be local or systemic, depending on the type of antigen and its location.
- The immune response and the immune cells' proliferation occur under a certain affinity threshold (the force that governs the coupling among antibodies and antigens).
- The clonal expansion process and somatic hypermutation produce immunological cells with high affinity to invaders antigens. These aspects are mainly exploited in the algorithm aiNet.

So, the driven processing of an AIS occurs through computationally implemented metaphors. Among some algorithms, there are the Artificial Immune NETwork (aiNet) and the CLONal ALGorithm selection (CLONALG), which are applied together in tasks such as learning machine, pattern recognition, compression and clustering [Silva, 2001]. The aiNet, illustrated in Figure 2, has its dynamics started with the supply of antigens (standards of training) and other parameters. In each iteration (generation), on applying the CLONALG algorithm, antibodies are produced (centers of a RBFNN) and are matched (represent) with a group of antigens (data to clustering). In each generation, the antibodies (which are initially random representations) are refined and/or created.

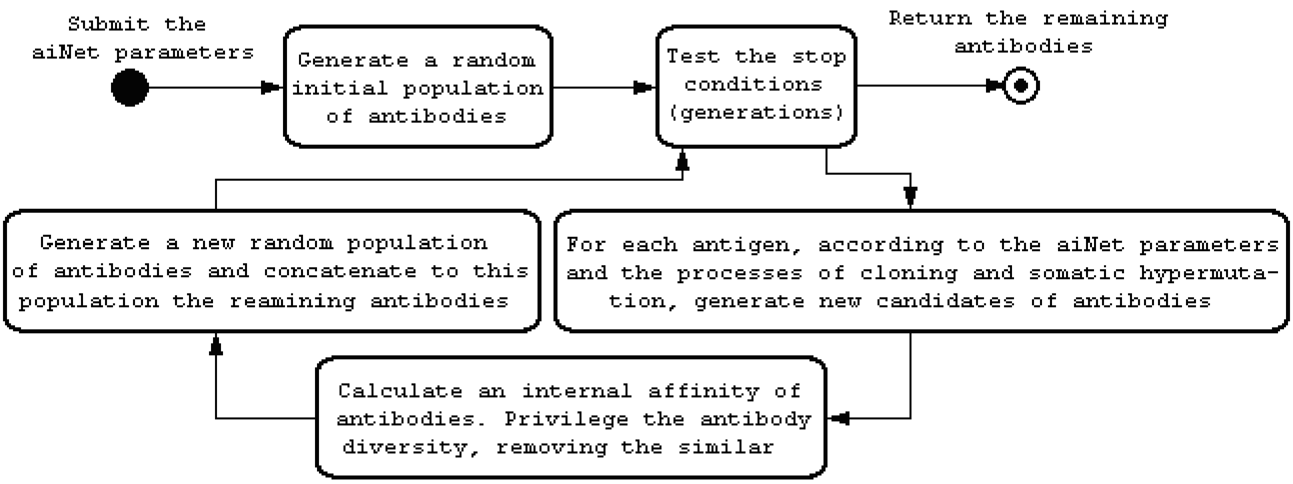

Figure 2: aiNet graphical representation(Adapted fromSilva [2001]).

In a RBFNN topology specification, it is noted that the aiNet adoption can overcome some important empirical issues, the determination of an optimal number of centers for the intermediary layer and at the same time suggests their initial location. In the next section, the practical content of this paper is discussed, where central issue resides on the iterative application process aiNet/k-means in the construction of a RBFNN.

Learning and Nonlinear Models - Revista da Sociedade Brasileira de Redes Neurais (SBRN), Vol. 4, No. 1, pp. -24-31, 2006

2.3 aiNet/k-means – an iterative hybrid method to construct optimal RBFNN

The method proposed to construct a RBFNN consists of five steps:

1. The input and output data are presented to the algorithm aiNet, with the algorithmic needed parameters;
2. The aiNet algorithm defines a set of initial centers (set of antibodies) for a RBFNN;
3. The initial centers are refined by the k-means algorithm, resulting in a set of "more affiants" antibodies as part of a problem solution;
4. The centers and output data are used to create a RBFNN;
5. The created RBFNN is tested with a new set of input and output data, taking into account the measured error rate to determine the retention of the best ANN solution.

The novelty of this method lies in the fact that steps 2 to 5 are iterative , taking into account the generation parameter of the aiNet algorithm. The adaptation of aiNet/k-means is shown in Figure 3.

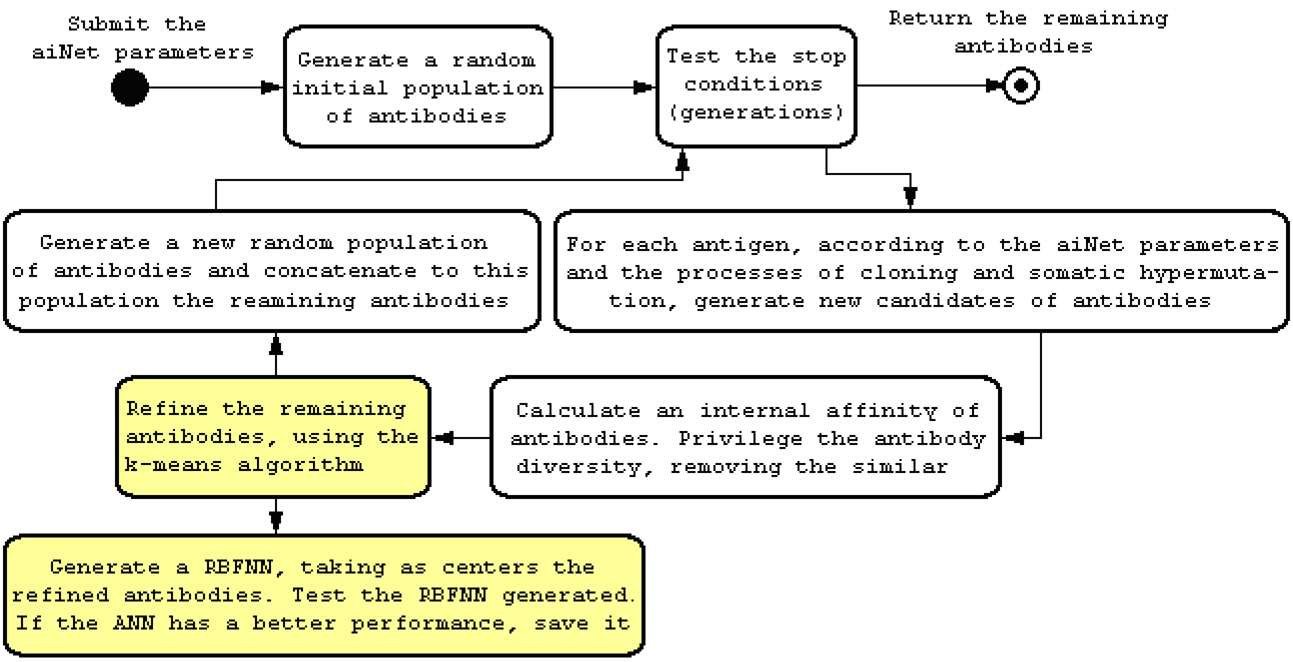

Figure 3: Graphical representation of aiNet/k-means iterative method.

An important factor to be considered is that the here suggested method is an exploration method of solutions, where time and computer resources variables are not considered in this paper.

To confirm or not that this is a valid strategy for the construction of a RBFNN , an initial classification experiment was carried out. With this experiment, two facts emerge:

i. The affinity of the antibodies taking into account the data center of mass (by applying the k-means algorithm) better represents the amount of input data (antigens), subsequently, this ensured a better minimization of the error rate; and
ii. The minor error rate occurred during the iterations of the standard aiNet algorithm or of the iterative aiNet/k-means, where the algorithms also define the optimal number of centers.

Figure 4 and Figure 5 illustrate these facts. Figure 4 shows the main steps of a particular iteration of the iterative aiNet/k-means iterative, highlighting the issue of better representation of antigens to the amount of input data after the refinement of the antibodies by the k-means algorithm. And Figure 5 shows that the minor error rate was not reached in the last iteration of the standard or modified aiNet algorithm.

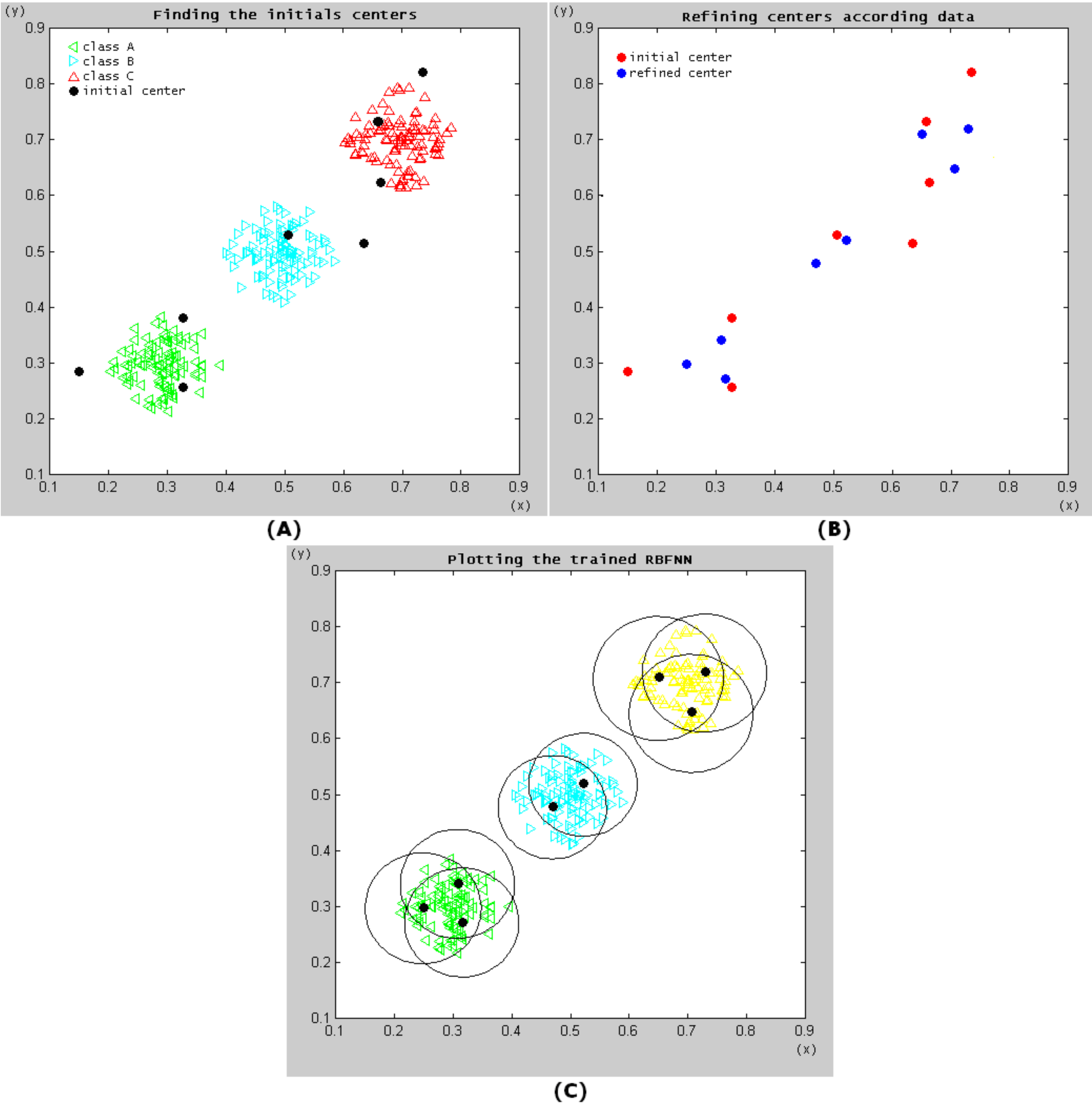

Figure 4: Main steps of an aiNet/k-means iterative method.

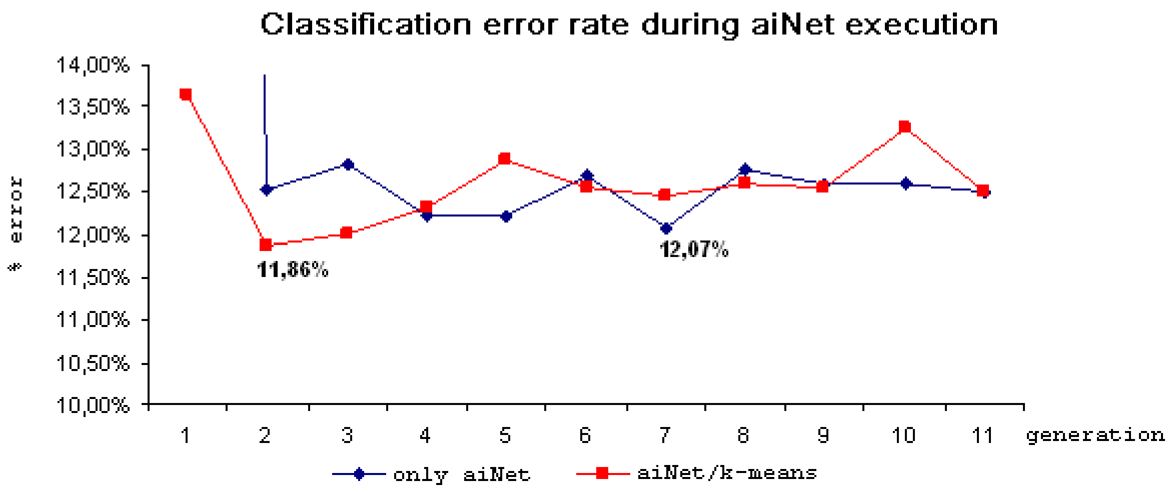

Figure 5: An illustrative experiment.

It is important to highlight that the implementations needed for the RBF construction method were based on and adapted from [Todesco 1995] and [Silva 2006].

3 Application and Results

The suggested application as the practical part of this study comes from a doctoral thesis [Tedesco, 1995], where the author uses a set of RBFNN for human chromosome classification. The available data consist of three chromosomal features taken as input (i.e. the length, the area and the centromere position of chromosomes) and the set of seven classes (Group of Denver) as output patterns. Table 1 shows that there were two databases available, each one divided into training and test datasets.

Table 1: Used data in experiments.

TUPLES' AMOUNT		
Data's source	**Training**	**Test**
Copenhagen	4061	4045
Edinburg	2682	2866

Similarly to Todesco (1995), only 1.000 (one thousand) records of data set were considered for the RBFNN training stage. In the testing stage, all records were considered. That was made aiming at ratifying the results in constructing a RBFNN with similar performance, as in the previous study.

Table 2 summarizes the iterative aiNet/k-means tests carried out and compares them with Todesco's results. Itis important to mention that the proposed method shows itself as a promising new method for finding minimized error rates automatically as an empirical searching tool, and also specifies an optimal match to a number of centers in the intermediary layer of a RBFNN, in a particular task. Therefore, in the experiment with Copenhagen's dataset it is automatically found 61 centers to the RBFNN with the best performance during the iterative process. Likewise Edinburg's dataset, it was found 66 centers as ideal number.

Table 2. Comparative results table - Todesco (1995) method used and the Hybrid method.

	COMPARATIVE TABLE (error rate)			
Data's source	**RBFNN trained only by k-means algorithm**			**Iterative aiNet/k-means**
	Empiric number of centers tested			
	50	75	100	
Copenhagen	5.40	5.44	5.36	5.33
Edinburg	11.55	11.48	12.25	11.58

To better show the achieved results, Figure 6 illustrates the development of the during the iterations, considering the number of created centers and error rates for each experiment. It can be noted that the best classification performance is achieved in the intermediate aiNet/k-means iterations.

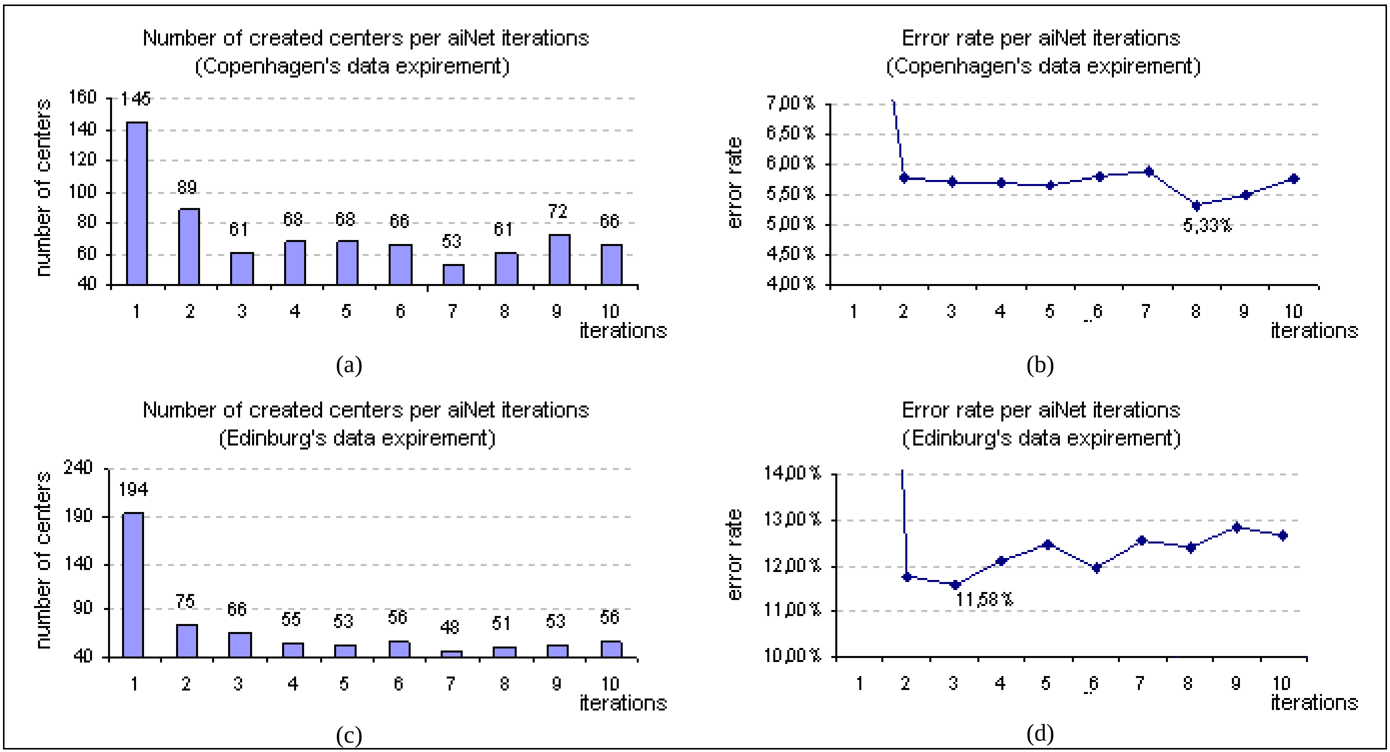

Figure 6: Evolution of iterative aiNet/k-means experiments.

4 Conclusions

From the results obtained with the aiNet-determination hybrid model described here, some benefits can be highlighted. One is the adulteration of empiricism in the determination of the inner functions of radial basis through a well-defined methodology for the use of the aiNet operator. Another advantage is the reduction to the number of samples for the determination of these centers, facilitating the task for the k-means algorithm, without additional parameters. An analysis that may merit further attention is the impact of the number of dimensions of the entry area, because there is a reduction in the number of samples, the complexity of time and space can be minimized.

The comparison between the basic model RBF / k-means and the hybrid model RBF / k-means / aiNet was measured by means of error classification. The comparison can be extended to future studies, and other indicators can be used as a broad approach to evaluation, such as generalized cross validation (Generalized Cross-Validation - GCV) and as criteria for Bayesian inference (Bayesian Inference Criterion). Further the databases of human chromosomes used in this work, other databases of common use can be used to test the classification tasks by the hybrid model.

Other ANN types can be used to build a hybrid model with AIS, such Multi-Layer Perceptron (MLP). Although it has reached a good method to determine the centers of the radial functions, it still remains open questions about how to determine radius or variance for these functions. This could be emphasized as an opportunity to continue improving the iterative aiNet/k-means method.

5 References

Alves, R. T, et al. (2004). Induction of Fuzzy Classification Rules with an Artificial Immune System, *Proceedings of SBRN - 8th Brazilian Symposium on Neural Networks*, CD_ROM.

Dasgupta, D. (1997). Artificial Neural Networks and Artificial Immune Systems: Similarities and Differences, *Proceedings of the IEEE SMC*, 1, p. 873-878.

Diao, Y; Passino, K, M. (2002). Immunity-based hybrid learning methods for approximator structure and parameter adjustment. *Engineering Applications of Artificial Intelligence*, v. 15, n. 6, p. 587-600.

Farmer, J. D., Packard, N e Perelson, A. (1986) The immune system, adaptation and machine learning, *Physica D*, v. 2, p. 187-204.

Feyereisl, J. and Aickelin, U. (2006). Artificial Immune Tissue using Self-Organizing Networks, *Proceedings of the Workshop on Artificial Immune Systems and Immune System Modelling*, p 5-6.

Nasaroui, O., et al. (2003). A Scalable Artificial Immune System Model for Dynamic Unsupervised Learning, Proceedings of the Genetic and Evolutionary *Computation Conference (GECCO)*, p. 219-230.

Pandya, A. S. (1995). *Pattern recognition with neural networks in C++*, CRC Press.

Silva, L. N. de C. (2006). Demo Manual. Disponível em: <http://www.dca.fee.unicamp.br/~vonzuben/research/lnunes_dout/softwares/demos/manual.htm>. Acesso em l, Maio.

Silva, L. N. de C and Zuben, F. J. von (2001). An Immunological Approach to Initialize Centers of Radial Basis Function Neural Networks, Proceedings of CBRN 2001 - *V Brazilian Conference on Neural Networks*, p. 79-84.

Silva, L. N. de C, ZUBEN, F. J. von (2006). Artificial Immune Systems: Part II – a Survey of Application. Disponivel em: <http://www.dca.fee.unicamp.br/~vonzuben/research/lnunes_dout/relatorios/rtdca0200.pdf>. Acesso em 5, Maio.

Silva, L. N. de C. (2001). Engenharia Imunológica: Desenvolvimento e Aplicação de Ferramentas Computacionais inspiradas em Sistemas Imunológicos Artificiais, Tese (doutorado) - *Universidade Estadual de Campinas, Faculdade de Engenharia Elétrica e de Computação, Campinas*.

Timmis, J (2004). Exploiting the Immune System for Computation, *IEEE Intelligent Informatics Bulletin*, Vol. 4 n. 2, p. 1-2.

Todesco, J. L. (2006). Introdução à Inteligência Aplicada – Redes Neurais. Disponivel em: <http://www.inf.ufsc.br/~tite/IA/Aula6/RedesNeurais.pdf>. Acesso em 5, Maio.

Todesco, J. L. (1995). Reconhecimento de padrões usando rede neuronal artificial com uma função de base radial: uma aplicação na classificação de cromossomos humanos, *Tese (Doutorado em Engenharia de Produção) - Engenharia de Produção e Sistemas, UFSC*, Florianópolis.