

Engineering Applications of Artificial Immune Systems

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Topics



- Engineering Problems and Their Challenges
- Examples of Engineering Problems
- Engineering Applications of AIS: Brief Survey from the Literature
- Examples of Engineering Applications of AIS from our Research Labs
- Discussion

Affiliations (Labs Involved in this Research)



Catholic University of Santos



Wernher von Braun Center
for Advanced Research



Bioinformatics and Bio-Inspired
Computing Laboratory



Natural Computing Lab

Part I

Engineering Problems and Their Challenges

Engineering Problems

- Real-World Problems
- An imprecise and incomplete classification:
 - Pattern Recognition and Classification
 - Machine Learning
 - Data Mining
 - Search and Optimization
 - Robotics
 - Control
 - Industrial Applications

Engineering Problems

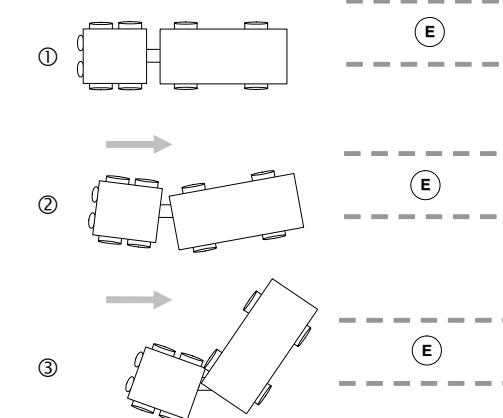
- Some Common Features:
 - Difficulty in modelling
 - Poorly defined
 - Dynamic environments
 - Large number of variables
 - Missing or noisy variables (attributes)
 - Highly nonlinear
 - Difficulty in finding derivatives
 - Combinatorial solutions (NP-Complete/NP-Hard)

Part II

Examples of Engineering Problems

Examples of Engineering Problems

- Non-Linear Control



Examples of Engineering Problems



- Pattern Recognition



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9

Examples of Engineering Problems



- Autonomous Navigation



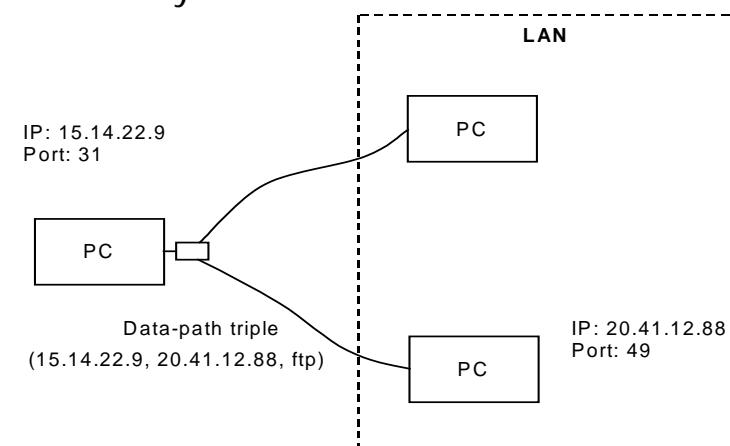
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10

Examples of Engineering Problems



- Anomaly Detection



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Examples of Engineering Problems



- Scheduling



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12

Part III

Engineering Applications of AIS: A Brief Survey from the Literature

- Pattern Recognition and Classification / Machine Learning / Data Mining:
 - Spectra Recognition
 - Dasgupta et al., 1999
 - Surveillance of Infectious Diseases
 - Tarakanov et al., 2000
 - Medical Data Analysis
 - Carter, 2000
 - Virus Detection and Elimination
 - Kephart, 1994
 - Somayaji et al., 1997
 - Okamoto & Ishida, 1999
 - Lamont et al., 1999

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14

Engineering Applications of AIS: Brief Survey from the Literature



- Pattern Recognition and Classification / Machine Learning / Data Mining:
 - Computer and Network Security
 - Kephart, 1994
 - Hedberg, 1996
 - Kim & Bentley, 1999
 - Dasgupta, 1999
 - Gu et al., 2000
 - Hofmeyr & Forrest, 2000
 - Skormin et al., 2001
 - Anchor et al., 2002
 - Dasgupta & González, 2002
 - Wang & Hirsbrunner, 2002
 - de Paula et al., 2004

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15

Engineering Applications of AIS: Brief Survey from the Literature



- Pattern Recognition and Classification / Machine Learning / Data Mining:
 - Time Series Data
 - Dasgupta & Forrest, 1996
 - Image Processing and Inspection
 - Aisu & Mizutani, 1996
 - McCoy & Devarajan, 1997
 - Sathyanath & Sahin, 2001
 - Bendiab et al., 2003
 - Web Mining
 - Lee et al., 2003
 - Secker et al., 2003
 - Oda & White, 2003

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16

- Pattern Recognition and Classification / Machine Learning / Data Mining:
 - Fault (Anomaly) Detection
 - Ishida, 1990
 - Kayama et al., 1995
 - Xanthakis et al., 1996
 - D'haeseleer et al., 1996
 - Bradley & Tyrrell, 2000
 - Shulin et al., 2002
 - Taylor & Corne, 2003
 - González et al., 2003
 - Esponda et al., 2003
 - Kaers et al., 2003
 - Araujo et al., 2003
 - Branco et al., 2003

- Pattern Recognition and Classification / Machine Learning / Data Mining:
 - Learning
 - Watkins, 2001
 - Hunt & Cooke, 1996
 - Hightower et al., 1996
 - Potter & de Jong, 1998
 - Bersini, 1999
 - Nagano & Yonezawa, 1999
 - Timmis & Neal, 2000
 - de Castro & Von Zuben, 2000a
 - Watkins et al., 2004

- Pattern Recognition and Classification / Machine Learning / Data Mining:
 - Associative Memory
 - Gibert & Routen, 1994
 - Abbattista et al., 1996
 - Recommender System
 - Cayzer & Aickelin, 2004
 - Inductive Problem Solving
 - Slavov & Nikolaev, 1998
 - Bankruptcy Prediction
 - Cheh, 2002

- Pattern Recognition and Classification / Machine Learning / Data Mining:
 - Clustering/Classification
 - Nicosia et al., 2001
 - Timmis, 2001
 - de Castro & Timmis, 2002
 - Neal, 2002
 - Zhao & Huang, 2002
 - Greensmith & Cayzer, 2003
 - Ceong et al., 2003
 - Di & Xuefeng, 2003
 - Nasaroui et al., 2002, 2003

Engineering Applications of AIS: Brief Survey from the Literature



- Pattern Recognition and Classification / Machine Learning / Data Mining:
 - Bioinformatics
 - Recognition of promoter sequences: Cooke & Hunt, 1995
 - Protein structure prediction: Michaud et al., 2001
 - Spectra classification: Lamont et al., 2004
 - Gene expression data analysis: Bezerra & de Castro, 2003; Shin, 2003
 - Analysis of biological systems: Roy et al., 2002
 - Bioarrays: Tarakanov et al., 2002

Engineering Applications of AIS: Brief Survey from the Literature



- Search and Optimization:
 - Numerical Function Optimization
 - Mori et al., 1993
 - Bersini & Varela, 1990
 - Chun et al., 1998
 - Huang, 2000
 - Gaspar & Hirsbrunner, 2002
 - de Castro & Von Zuben, 2002
 - de Castro & Timmis, 2002
 - Hong & Zong-Yuan, 2002
 - Walker & Garrett, 2003

Engineering Applications of AIS: Brief Survey from the Literature



- Search and Optimization:
 - Constrained Optimization
 - Hajela & Yoo, 1999
 - Inventory Optimization
 - Joshi, 1995
 - Time Dependent Optimization
 - Gaspar & Collard, 2000
 - Others
 - Mori et al., 1997, 1998
 - Huang, 2000

Engineering Applications of AIS: Brief Survey from the Literature



- Search and Optimization:
 - Combinatorial Optimization
 - Mori et al., 1998
 - Endoh et al., 1998
 - Toma et al., 1999
 - Hart & Ross, 1999
 - King et al., 2001
 - Cui et al., 2001
 - Costa et al., 2002
 - Coello Coello et al., 2003
 - Cutello et al., 2003
 - Koko et al., 2003

- Robotics:
 - Autonomous Navigation
 - Watanabe et al., 1999
 - Michelan & Von Zuben, 2002
 - Hart et al., 2003
 - Vergas et al., 2003
 - Canham et al., 2003
 - Collective Behavior
 - Mitsumoto et al., 1996
 - Lee & Sim, 1997
 - Walking Robots
 - Ishiguro et al., 1998

- Control:
 - Identification, Synthesis and Adaptive Control
 - Bersini, 1991
 - Ishida & Adachi, 1996
 - Krishnakumar & Neidhoefer, 1999
 - Ding & Ren, 2000
 - Kim, 2001
 - Lau & Wong, 2003
 - Sequential Control
 - Ootsuki & Sekiguchi, 1999
 - Feedback Control
 - Takahashi & Yamada, 1997

- The references from this brief and incomplete survey can be found at:
 - www.dca.fee.unicamp.br/~lnunes/AIS.html
- An extensive and constantly updated bibliography on AIS can be found at:
 - http://ais.cs.memphis.edu/papers/ais_bibliography.pdf



Part IV

Examples of Engineering
Applications of AIS from Our Labs

Examples of Engineering Applications of AIS from our Labs



- Search and Optimization
 - Multimodal search
 - Dynamic environments*
 - Blind equalization
- Pattern Recognition and Classification
 - Classification and clustering
 - Detection of buffer overflow attacks

Examples of Engineering Applications of AIS from our Labs

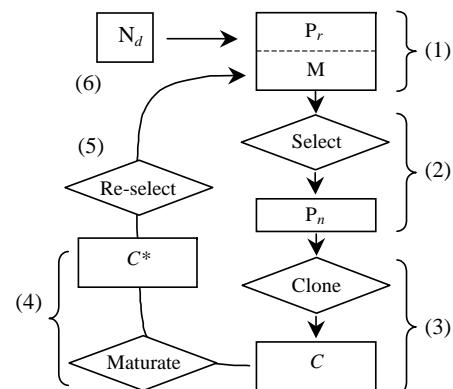


- Machine Learning
 - Neural network initialization
 - Neural network training*
 - Hybrid neural networks
- Robotics
 - Autonomous navigation
- Bioinformatics
 - Gene expression data analysis

Search and Optimization



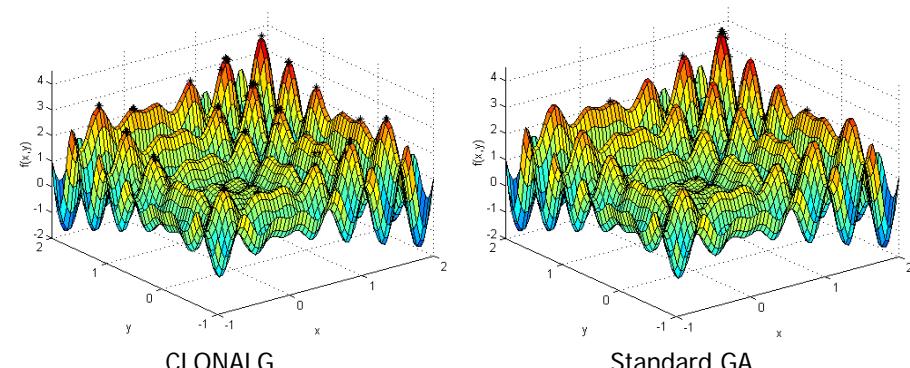
- Multimodal Search
 - CLONALG (de Castro & Von Zuben, 2002)



Search and Optimization

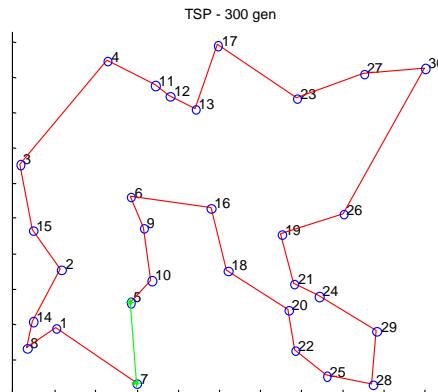


- Multimodal Search
 - CLONALG (de Castro & Von Zuben, 2002)



Search and Optimization

- Combinatorial Search
 - CLONALG (de Castro & Von Zuben, 2002)

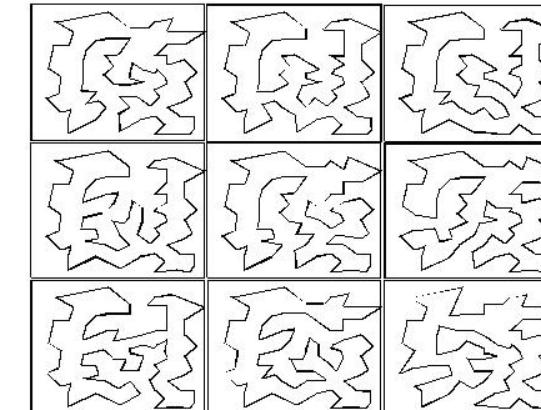


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33

Search and Optimization

- Combinatorial Search
 - Copt-aiNet (de Sousa et al., 2004)



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34

Search and Optimization

- CLONALG (de Castro & Von Zuben, 2002)

DEMO 1: CLONALG

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35

Search and Optimization

- Multimodal Search
 - opt-aiNet (de Castro & Timmis, 2002)
 - The algorithm for opt-aiNet is an adaptation of a discrete artificial immune network usually applied in data analysis
 - Features of opt-aiNet:
 - population size dynamically adjustable
 - exploitation and exploration of the search-space
 - capability of locating multiple optima
 - automatic stopping criterion

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36

Search and Optimization

- Multimodal Search

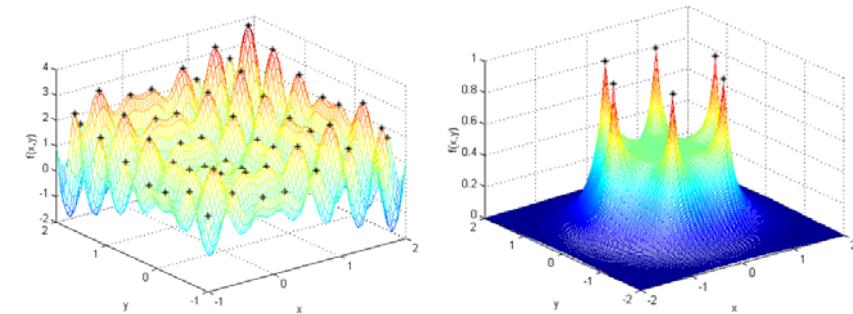
- opt-aiNet (de Castro & Timmis, 2002)

1. Initialize population (initial number not relevant)
2. **While** not [constant memory population], **do**
 - 2.1 Calculate fitness and generate clones for each network cell.
 - 2.2 Mutate clones proportionally to fitness and determine the fitness again.
 - 2.3 Calculate the average fitness.
 - 2.4 **If** average fitness does not vary, then continue. **Else**, return to step 2.1
 - 2.5 Calculate the affinity among cells and suppress all but one whose affinities are less than the suppression threshold σ_s and determine the number of network cells after suppression.
 - 2.6 Introduce a percentage of randomly generated cells and return to step 2.
3. **EndWhile**

Search and Optimization

- Multimodal Search

- opt-aiNet (de Castro & Timmis, 2002)



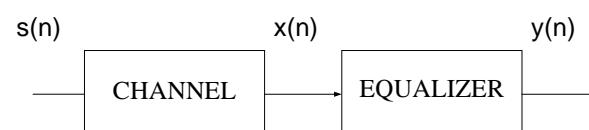
Search and Optimization

- Communications Engineering

- Search for the optimal Wiener equalizer
- opt-aiNet (Attux et al., 2003)

- Optimal Wiener Equalizer

- $y(n) = \mathbf{w}^T \cdot \mathbf{x}(n)$
- $J_W = E\{|s(n-d) - y(n)|^2\}$



Search and Optimization

- Optimal Wiener Equalizer

- The Constant Modulus (CM) criterion is used for blind equalization
- To find the CM global optimum is equivalent to determining the optimal Wiener solution (best equalizer)
- CM results in a multi-modal problem
- $J_{CM} = E\{[R_2 - |y(n)|^2]^2\}$

$$R_2 = \frac{E[|s(n)|^4]}{E[|s(n)|^2]}$$

Search and Optimization

- Optimal Wiener Equalizer via CM Search
- Sample performance
 - $H_{C1} = 1 + 0.4z^{-1} + 0.9z^{-2} + 1.4z^{-3}$

Solution	MSE	Freq. (GA+niching)	Freq. (opt-aiNet)
W_{opt}	0.1293	48 %	82%
W_2	0.1397	22 %	17%
W_3	0.1445	12 %	1 %
W_4	0.1533	10 %	-
W_5	0.1890	4 %	-
W_6	0.1951	4 %	-

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41

Search and Optimization

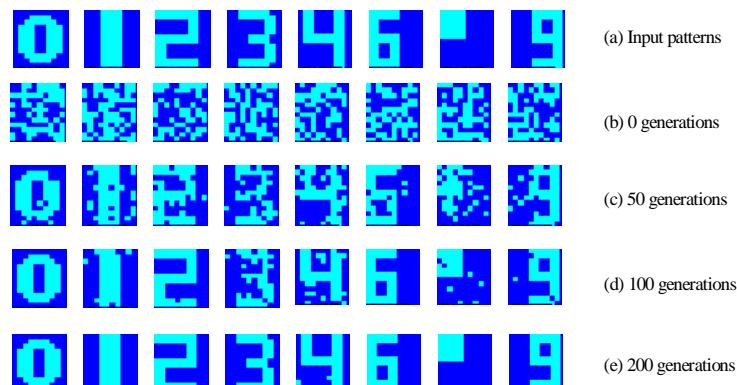
- opt-aiNet (de Castro & Timmis, 2002)
- DEMO 2: opt-aiNet**

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42

Pattern Recognition

- Classification and Clustering
 - CLONALG (de Castro & Von Zuben, 2002)



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43

Pattern Recognition

- Classification and Clustering
 - aiNet (de Castro & Von Zuben, 2000)
- Definition:
 - aiNet is an *edge-weighted graph*, not necessarily fully connected, composed of a set of nodes and sets of node pairs with a weight assigned specified to each connected edge.
- Features:
 - knowledge distributed among cells
 - competitive learning (unsupervised)
 - constructive model with pruning phases
 - generation and maintenance of diversity

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44

Pattern Recognition

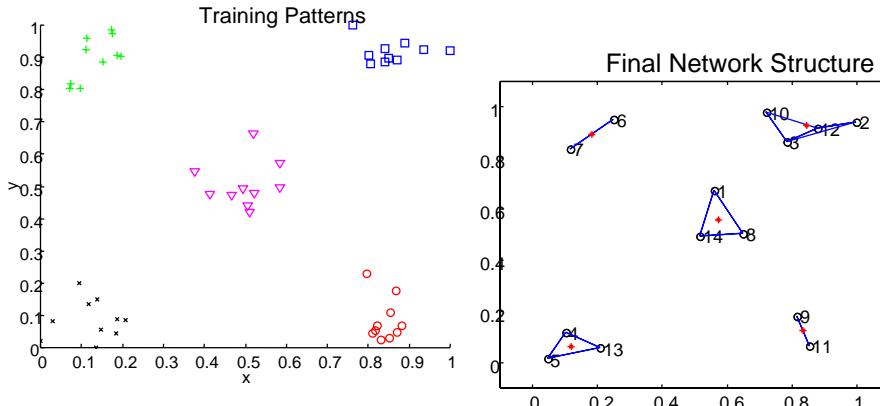
- aiNet:
 - Growing:
 - clonal selection principle
 - Learning:
 - directed affinity maturation
 - Pruning:
 - immune network theory

Pattern Recognition

- aiNet at each generation:
 - For each Ag
 - ① Affinity with the antigen (A_i) Ag_i -**Ab**
 - ② Clonal selection (n cells) $\propto A_i$
 - ③ Cloning $\propto A_i$
 - ④ Directed maturation (mutation) $\propto 1/A_i$
 - ⑤ Re-selection ($\zeta\%$) $\propto A_i$
 - ⑥ Natural death (σ_d) $\propto 1/A_i$
 - ⑦ Affinity between the network cells (D_{ij}) **Ab-Ab**
 - ⑧ Clonal suppression (σ_s) $\propto D_{ij}$: (m - memory)
 - ⑨ $M_t \leftarrow [M_t; m]$
 - Network suppression (σ_s) $\propto D_{ij}$: ($M \subseteq M_t$)
 - $M \leftarrow [M; \text{meta}]$

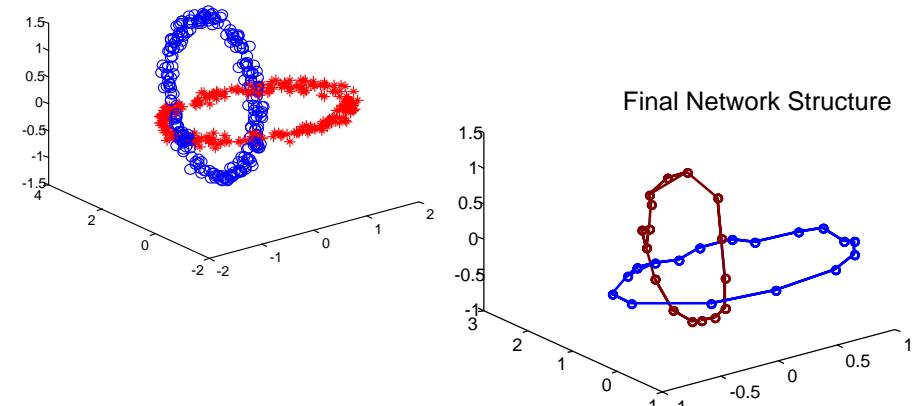
Pattern Recognition

- Clustering



Pattern Recognition

- Clustering



Pattern Recognition

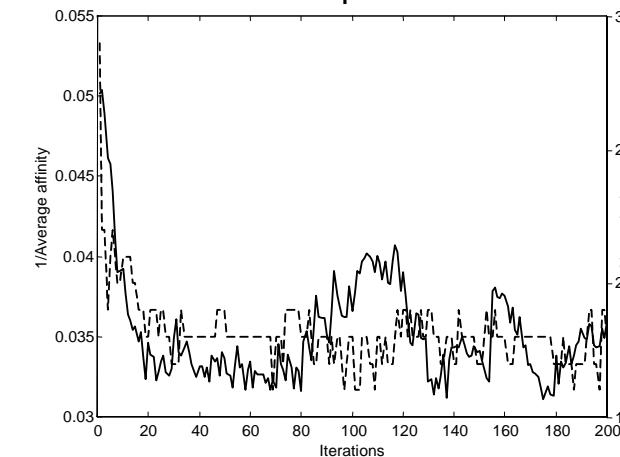
- The Immune Response of aiNet
- Network Hypotheses Used in aiNet
 - Clonal selection, expansion and maturation to foreign stimulation
 - Network interactions (suppression)
 - Network metadynamics
- Dynamics: Mix between learning and evolution

$$Ab_k^* = Ab_k + \alpha_k (Ag - Ab_k); \alpha_k \propto Aff_k; k = 1, \dots, Nc.$$

$$\Delta Ab = Nc - Ns + Nb - Nd$$

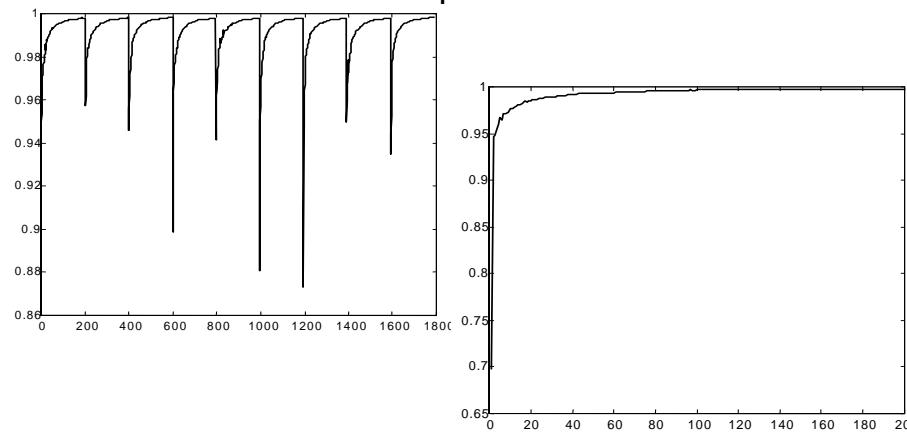
Pattern Recognition

- The Immune Response of aiNet



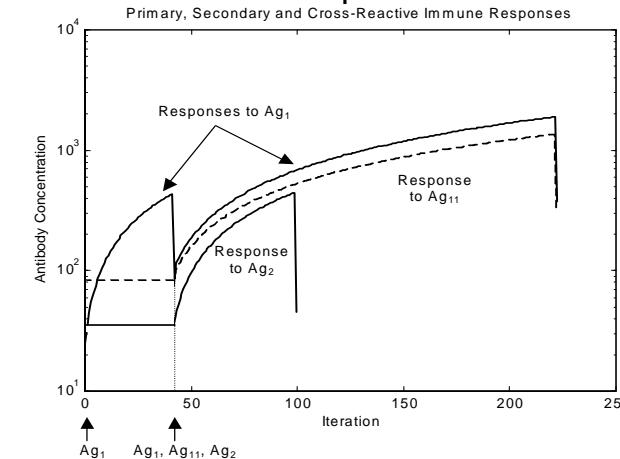
Pattern Recognition

- The Immune Response of aiNet



Pattern Recognition

- The Immune Response of aiNet



Pattern Recognition



- aiNet (de Castro & Von Zuben, 2000)

DEMO 3: aiNet

Pattern Recognition



- Detection of Buffer Overflow Attacks
 - ADENOIDS (de Paula et al., 2004)
 - An ID framework inspired by the architecture of the immune system
 - Prototype of an IDS based on the proposed framework
 - Elaborates on some ideas from Aickelin et al., 2002 about the Danger Theory as a missing link for AIS

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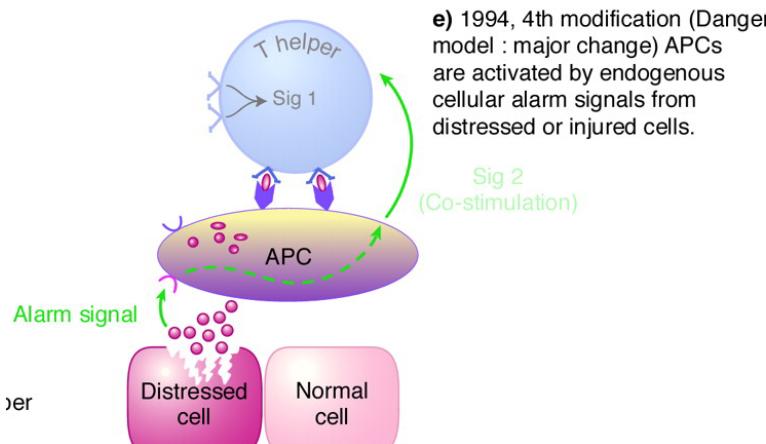
53

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54

Pattern Recognition

- Danger Theory (Matzinger, 2000)



Pattern Recognition



- Detection of Buffer Overflow Attacks
 - Desirable features based on the immune system (danger theory)
 - Automated intrusion recovery
 - Attack signature extraction
 - Potential to improve behavior-based detection

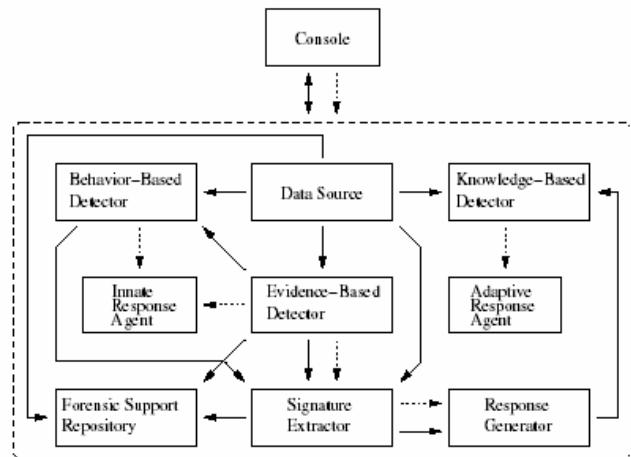
55

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56

Pattern Recognition

- Framework for Intrusion Detection



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57

Machine Learning

- Neural Network Initialization
 - SAND (de Castro & Von Zuben, 2001)
- Initial neural network (NN) weights:
 - learning speed
 - generalization performance
- Correlation: initial set of weights and initial repertoire of immune cells and molecules
- SAND: a Simulated ANnealing model to increase population Diversity

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58

Machine Learning

- Neural Network Initialization

- Affinity measure: $ED = \sqrt{\sum_{i=1}^L (x_i - y_i)^2}$

- Proposed cost (energy) function:

$$\bar{\mathbf{I}} = \frac{1}{N} \sum_{i=1}^N \mathbf{I}_i$$

- Average unit vector

$$\bar{R} = (\bar{\mathbf{I}}^T \bar{\mathbf{I}})^{1/2}$$

- Resultant vector (distance from the origin of the coordinate system)

$$E(\%) = 100 \times (1 - \bar{R})$$

- Percentage energy

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59

Machine Learning

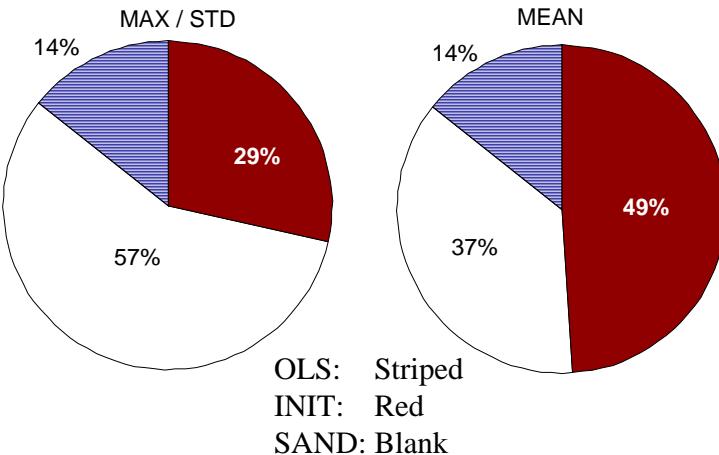
- Neural Network Initialization
 - Ab \rightarrow weight vector
 - Diverse antibodies in $\Re^L \rightarrow$ neurons with well distributed weight vectors in \Re^L
- SAND is applied separately to each network layer
- The vectors (Ab) have unitary norms and can be normalized to avoid neuron saturation

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60

Machine Learning

- Neural Network Initialization



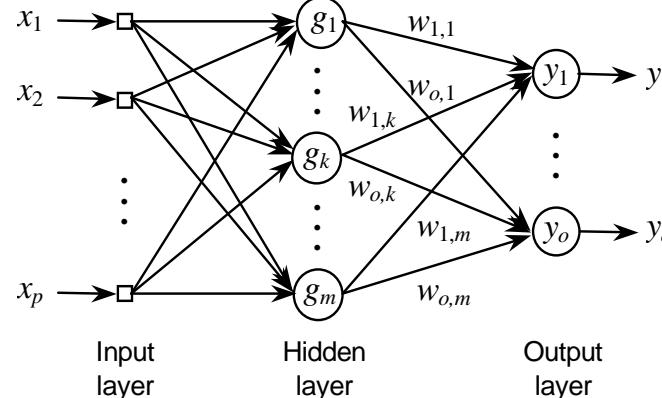
Machine Learning

- RBF Neural Network Center Selection
 - de Castro & Von Zuben, 2001
- The performance of the RBF neural network depends on the number, positions and dispersions of the basis functions composing the network hidden layer
- Traditional methods:
 - randomly choose input vectors from the training data set;
 - vectors obtained from unsupervised clustering algorithms;
 - vectors obtained by supervised learning schemes.

Machine Learning

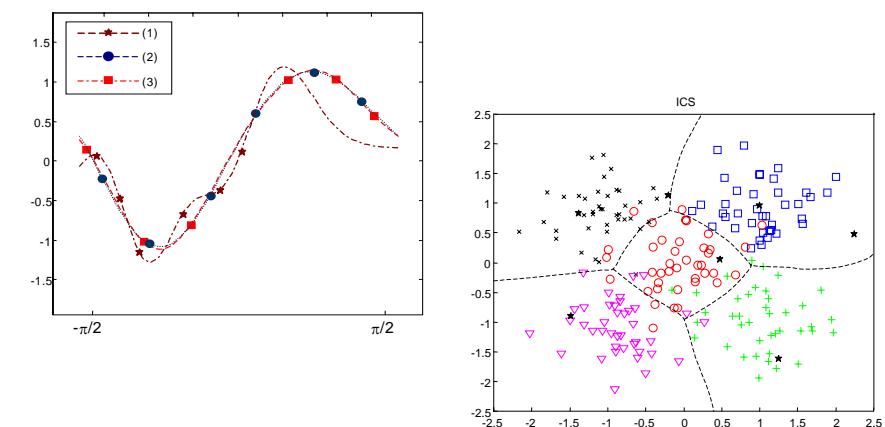
- RBF Neural Network Center Selection

- Solution based on aiNet



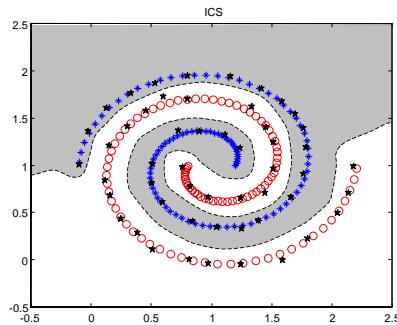
Machine Learning

- RBF Neural Network Center Selection



Machine Learning

- RBF Neural Network Center Selection

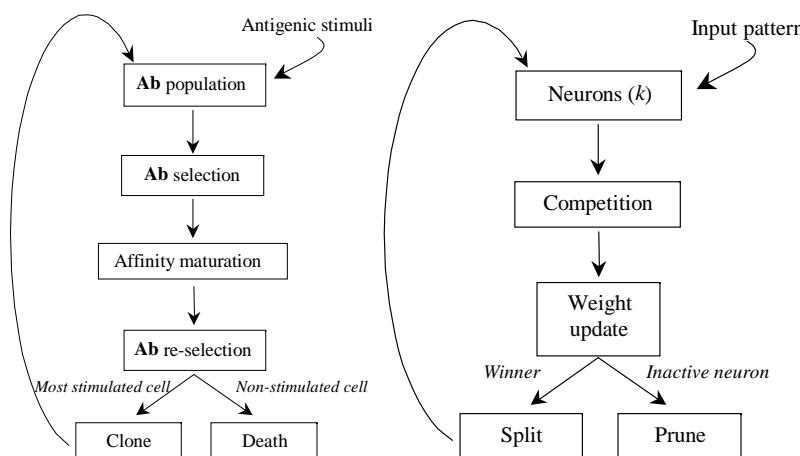


Method	Etr (%)	Ete (%)	M_1
ICS	0.0	0.0	7
MSBFN	-----	2.9	5
ELEANNE 2	0.0	1.3	11
Gradient descent	1.3	1.3	7

Iris data set
Best performance

Machine Learning

- ABNET



Machine Learning

- Boolean Neural Network (ABNET)

- de Castro et al., 2003

- Main Features:

- clustering, or grouping of similar patterns
- capability of solving binary tasks
- growing learning with pruning phases

- Main loop of the algorithm

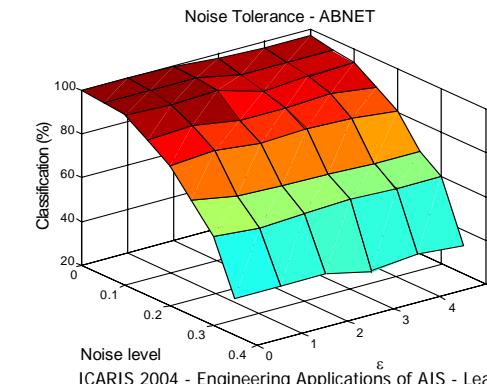
- Choose randomly an antigen (pattern)
- Determine the cell Ab_k with highest affinity
- Update the weight vector of this cell
- Increase the concentration level (τ_j) of this cell
- Attribute $V_a = k$

Machine Learning

- ABNET

- Binary character recognition

Noise tolerance:



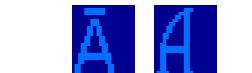
2) Cross-reactivity
(generalization)



(a) $\epsilon \geq 13.75\%$

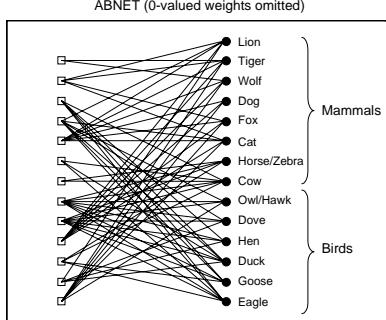


(b) $\epsilon \geq 13.75\%$



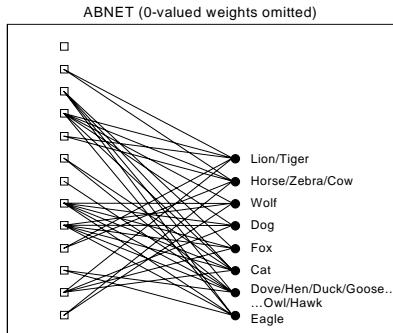
Machine Learning

- ABNET
 - Animals data set



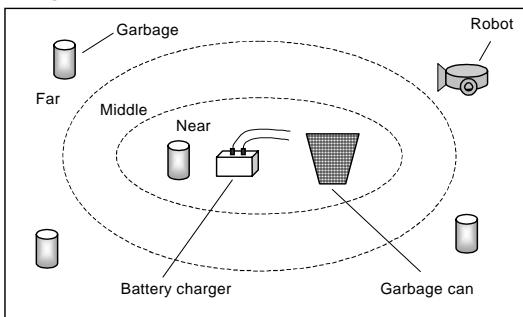
Machine Learning

- ABNET (de Castro et al., 2003)
DEMO 4: ABNET



Robotics

- Autonomous Navigation based on AIS
 - Michelan & Von Zuben, 2002
- Based on the works:
 - Ishiguro et al., 1996; Farmer et al., 1986

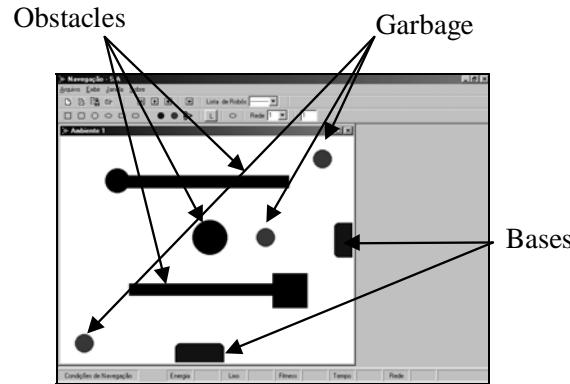


Robotics

- Autonomous Navigation based on AIS
 - Autonomous control system of a mobile robot based on the immune network theory
 - Each network node corresponds to a specific antibody and describes a particular control action for the robot
 - The antigens are the current state of the robot
 - The network dynamics corresponds to the variation of antibody concentration levels, which change according to both mutual interaction of antibody nodes and of antibodies and antigens
 - It is proposed an evolutionary mechanism to determine the network configuration

Robotics

- Autonomous Navigation based on AIS



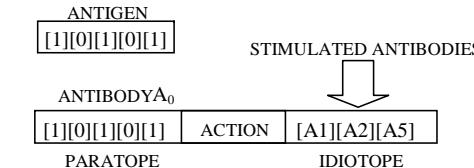
Robotics

- Autonomous Navigation based on AIS

- Objectives of navigation

$$E(t) = E(t-1) - E_{step} - E_{collision} - E_{garbage}$$

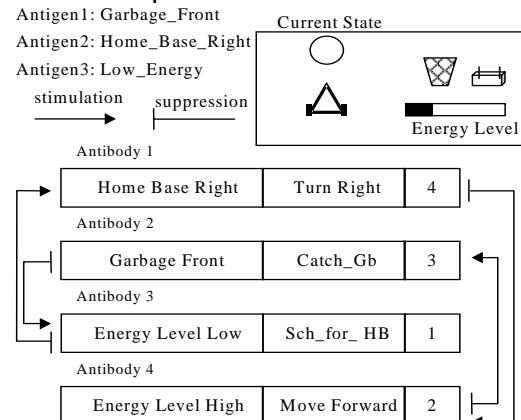
- Antibody structure



Robotics

- Autonomous Navigation based on AIS

- Network example



Robotics

- Autonomous Navigation based on AIS

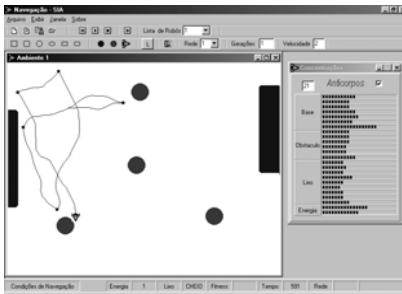
- Dynamics

$$\frac{dA_i(t)}{dt} = \left(\sum_{j=1}^N m_{ji} a_j(t) - \sum_{k=1}^N m_{ik} a_k(t) + m_i - k_i \right) a_i(t)$$

$$a_i(t+1) = \frac{1}{1 + \exp(0.5 - A_i(t))}$$

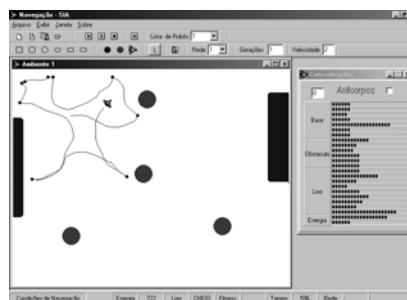
Robotics

- Autonomous Navigation based on AIS



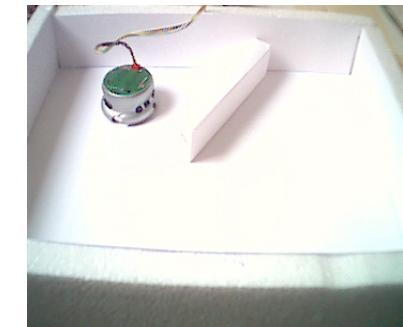
Immune network

Evolved network



Robotics

- Autonomous Navigation based on AIS
 - Implementation on Khepera II®: Vargas et al., 2003



Robotics

- Autonomous Navigation (Vargas et al., 2003)

DEMO 5: Collision Avoidance

Bioinformatics

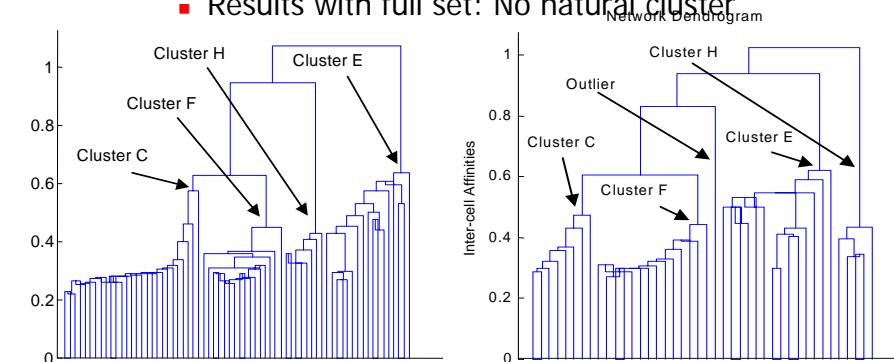
- Gene Expression Data Analysis
 - Bezerra & de Castro, 2003
 - de Sousa et al., 2004
- The Problem
 - Clustering gene expression data
 - Recent approach in bioinformatics that surged with the development of the DNA Microarrays
- DNA Microarrays
 - Experimental technique that measures the expression level of many genes simultaneously
 - A quantitative change in the scale of the experiments led to a qualitative change in the analyses, where the genes may be studied under a genome wide perspective

Bioinformatics

- Gene Expression Data Analysis
- Genes belonging to the same cluster may, among other things
 - Share the same regulatory system
 - Have similar properties or functions
 - Code products that interact physically
- Experimental Data
 - Gene expression data of the budding yeast *Saccharomyces cerevisiae*, obtained from Eisen et al. (1998)
 - Total of 2467 genes in 79 different conditions

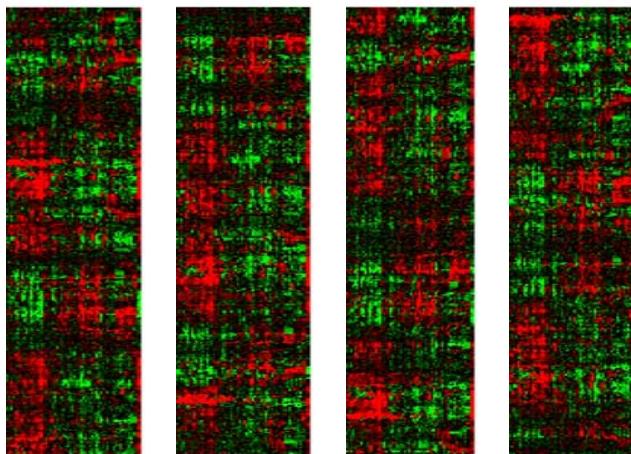
Bioinformatics

- Gene Expression Data Analysis
 - Clusters initially analyzed C, E, F and H (68 genes)
 - Results with full set: No natural cluster



Bioinformatics

- Multiple Simultaneous Views



Part V

Discussion

Discussion

- Vast number of applications available
- Great potential for further applications and developments
- Some issues that still deserve investigation:
 - Formal aspects
 - Comparison (theoretical and empirical) with other approaches
 - Loads of testing
 - Real benefits (Are they really useful?)
 - Danger theory
 - How far to stretch the metaphor?

Discussion

- Current trends in our labs
 - Improvements on the many versions of aiNet
 - Optimization on dynamic environments
 - Bioinformatics, mainly gene expression data analysis
 - Feedforward neural network training
 - Danger theory
 - Anomaly detection
- This Tutorial on the Web:
 - www.dca.fee.unicamp.br/~Inunes/AIS.html