A Brief Account on Morphological Perceptron with Competitive Layer Trained by a Certain Genetic Algorithm

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Summary

Abstract

Introduction

MP/CL

- Topology and Node Characteristics
- Learning Rule
- Characteristics

Morphological Perceptron with Genetic Algorithm

- Revision of GA
- MP/GA

Experimental Results

Concluding Remarks

Acknowledgment

Abstract

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We propose a learning strategy based on a certain genetic algorithm to circumvent the overfitting problem of the Morphological Perceptron with Competitive Learning (MP/CL).

Introduction

Neural Networks

- Machines partially inspired by the human brain
- Basic processing units: neurons
- Learning process
- Capacity of generalization
- Solve complex computation problems

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Morphological Perceptron with Competitive Learning - MP/CL

Topology and Node Characteristics

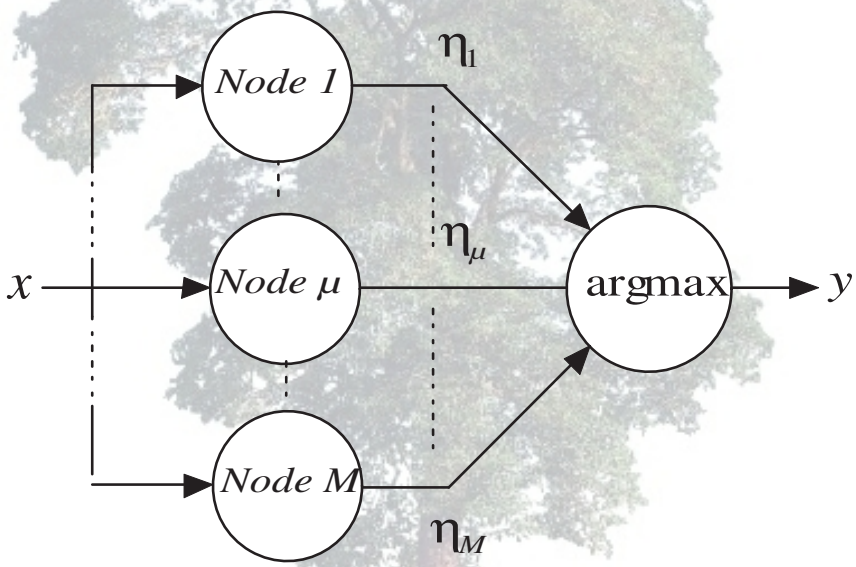

Figure 1: MP/CL network topology.

- The parameters of the μ-th node: $(\mathbf{a}_\mu, \mathbf{b}_\mu, \ell_\mu)$:
  - The weights of the μ-th:

$$\begin{aligned} \mathbf{a}_\mu^T &= [a_{\mu 1}, \ldots, a_{\mu N}] \\ \mathbf{b}_\mu^T &= [b_{\mu 1}, \ldots, b_{\mu N}] \end{aligned} \tag{1}$$

  - The μ-th node has a class label denoted by ℓ_μ.

Morphological Perceptron with Competitive Learning - MP/CL

Topology and Node Characteristics

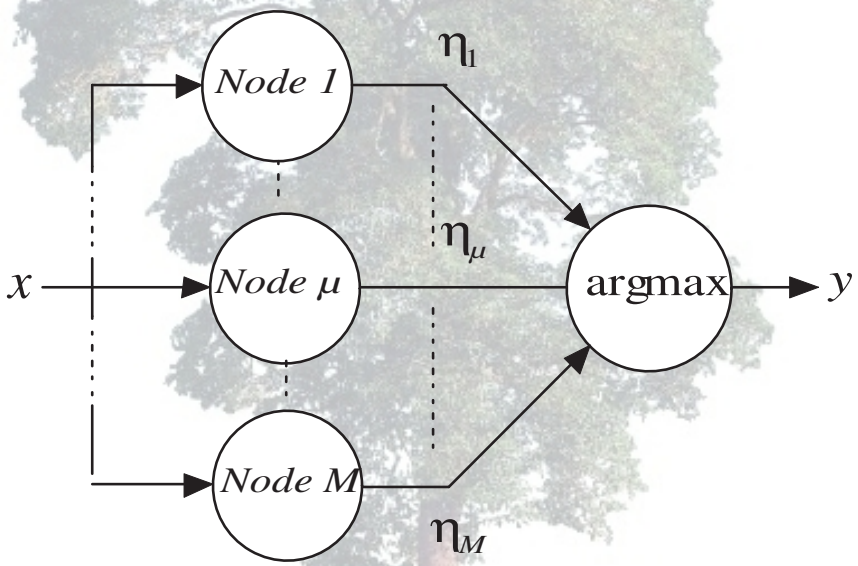

Figure 1: MP/CL network topology.

- Given a input pattern $\mathbf{x} = [x_1, \ldots, x_N]^T \in \mathbb{R}^N$, the individual output $\eta_\mu(\mathbf{x})$ is:

$$\eta_\mu(\mathbf{x}) = \min\left\{\min_{j=1:N}\{x_j - a_{\mu j}\}, \min_{j=1:N}\{b_{\mu j} - x_j\}\right\} \quad (1)$$

- The MP/CL assigns to the input pattern $\mathbf{x}$ the class label ℓ_{μ^*}, where μ^* denotes the first index μ such that $\eta_{\mu^*} = \max_{i=1:M} \eta_\mu(\mathbf{x})$.

Morphological Perceptron with Competitive Learning - MP/CL

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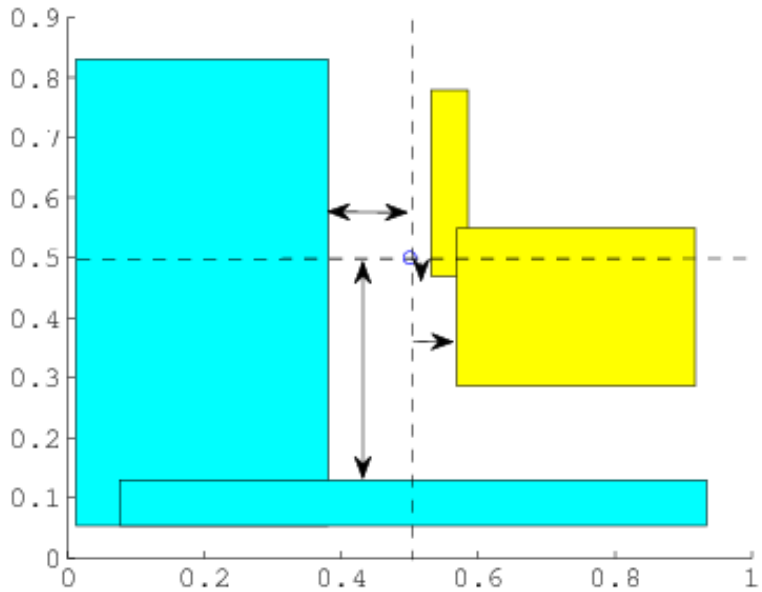

Figure 2: Example of how MP/CL works.

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Morphological Perceptron with Competitive Learning - MP/CL

Learning Rule

- Supervised learning:
  - The triple $(\mathbf{a}_\mu, \mathbf{b}_\mu, \ell_\mu)$ is determined using a training set $\mathcal{S}_{tr} = \{(\mathbf{x}_1, d_1), \ldots, (\mathbf{x}_K, d_K)\}$, where $\mathbf{x}_k \in \mathbb{R}^N$ belongs to class $d_k \in \{1, 2, \ldots, C\}$, for all $k = 1, \ldots, K$.

Morphological Perceptron with Competitive Learning - MP/CL

Characteristics

- Some interesting properties of MP/CL are:
  1. Convergence in a finite number of steps.
  2. Perfect separation of the training data according to their class labels.
  3. Hyperboxes with distinct class labels do not overlap.
  4. Independence of the order in which the training patterns are presented to the network.

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Revision of Genetic Algorithm - GA

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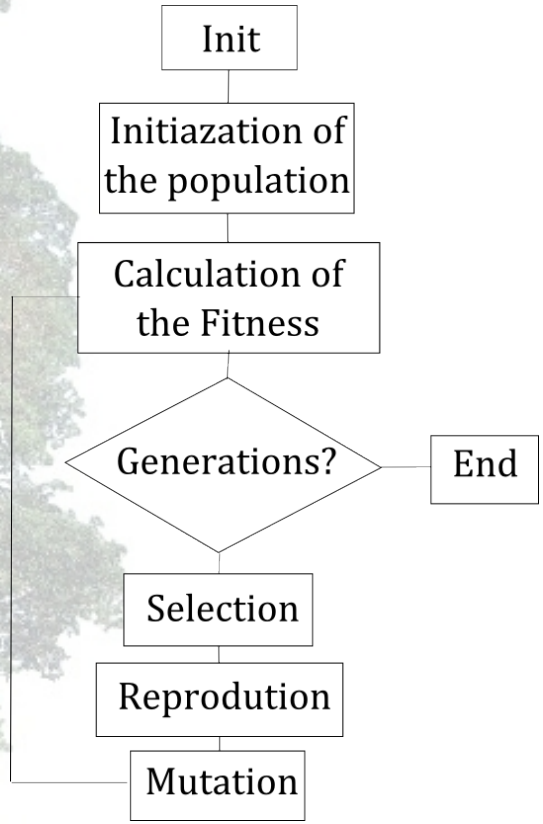

Figure 3: Genetic Algorithm.

MP/GA

Morphological Perceptron with Genetic Algorithm - MP/GA

- Population $\mathcal{P}(t) = \{\upsilon_1(t), \upsilon_2(t), \ldots, \upsilon_{pop_size}(t)\}$, where t is the iteration or generation number.
- υ_i corresponds to a MP/CL:

$$\upsilon_i = \{(\mathbf{a}_{1i}, \mathbf{b}_{1i}, \ell_{1i}), \ldots, (\mathbf{a}_{Mi}, \mathbf{b}_{Mi}, \ell_{Mi})\}, \tag{2}$$

  where M denotes the (fixed) number of nodes.
- Training Set $\mathcal{S}_{tr} = \{(\mathbf{x}_1, d_1), \ldots, (\mathbf{x}_K, d_K)\}$ is divided in two sets $\mathcal{S}_{tr}^H$ and $\mathcal{S}_{tr}^E$ such that $\mathcal{S}_{tr} = \mathcal{S}_{tr}^H \cup \mathcal{S}_{tr}^E$.
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MP/GA

- Each individual $\upsilon_i(0)$ of the initial population $\mathcal{P}(0)$ is a MP/CL whose nodes are defined as follows:
  - For each class $c \in \{1, \ldots, C\}$, we randomly select M_c data points $(\mathbf{x}_k, d_k) \in \mathcal{T}$ such that $d_k = c$
  - Define the μ-th node $(\mathbf{a}_\mu, \mathbf{b}_\mu, \ell_\mu) = (\mathbf{x}_k, \mathbf{x}_k, d_k)$.
- The crossover of υ_i and υ_j simply swaps nodes between the two individuals:

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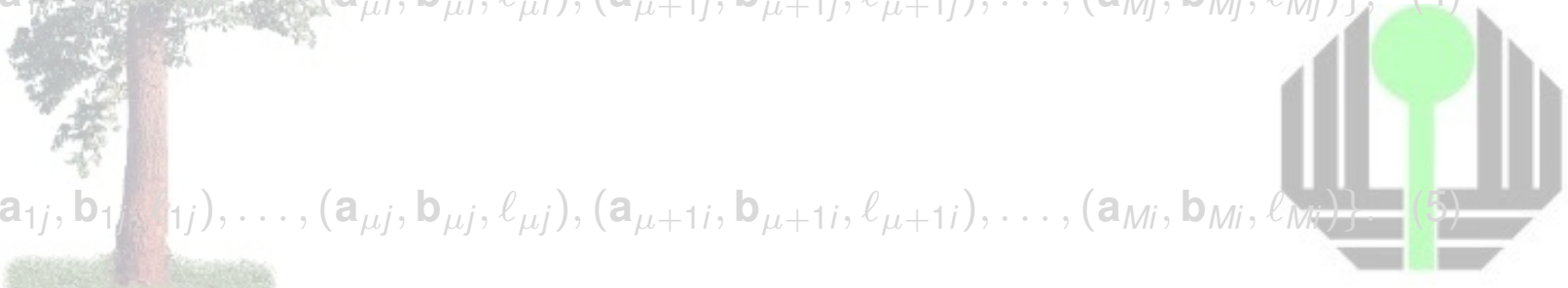

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MP/GA

- When an individual v'_j undergoes a mutation:
  - We determine the pattern $\mathbf{x}_{k^*}$ of $\mathcal{S}_{tr}^H$ that does not belong to the hyperbox $[\mathbf{a}_j, \mathbf{b}_j]$, but has the largest compatibility.
  - The bottom-left and top-right corners are modified if the node μ and the pattern $\mathbf{x}_{k^*}$ belong to the same class.

$$\mathbf{a}_\mu \leftarrow \min(\mathbf{a}_\mu, \mathbf{x}_{k^*}) \quad \text{and} \quad \mathbf{b}_\mu \leftarrow \max(\mathbf{b}_\mu, \mathbf{x}_{k^*}), \tag{6}$$

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Experimental Results

Parameters

- Roulette wheel as the selection process.
- Crossover probability of 0.3
- Mutation probability of 0.2
- Population size of 30.
- Maximum number of generations of 100.
- $S_{tr}^{E} = S_{tr}^{H} = S_{tr}^{K}$

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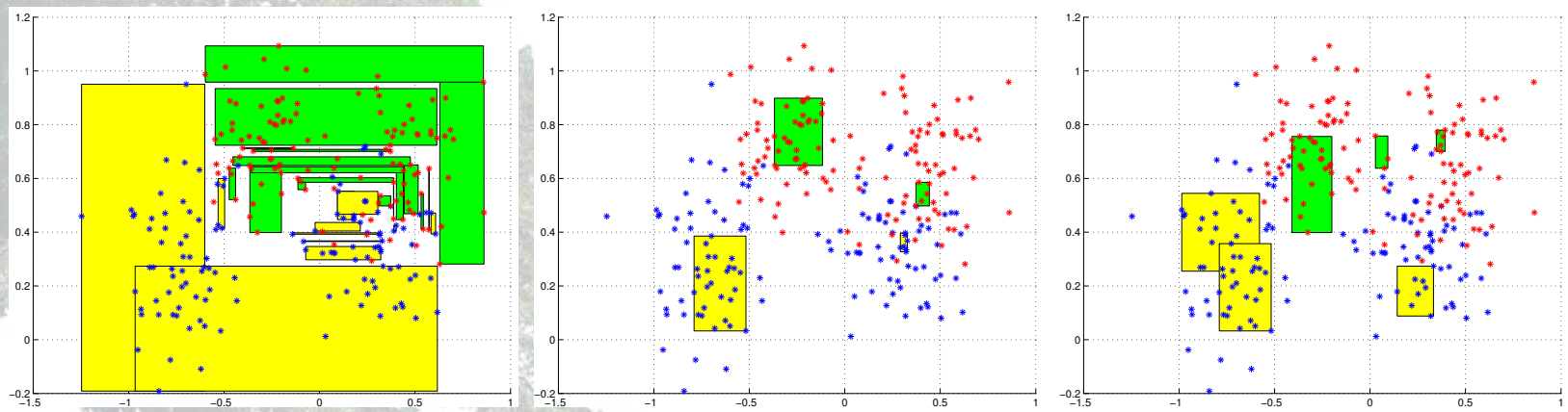
Experimental Results

Results

Experimental Results						
Problem	MP/CL			MP/GA		
	E_{tr}	E_{te}	M	E_{tr}	E_{te}	M
Ripley's Problem				17.47	9.8	1+1
	0	10.2	26+29	15.06	10	3+3
Iris	0	0	14	2.86	0	6
Breast Cancer	0	4.07	64	6.02	4.07	40

Table 1: Results from experimental tests using MP/GA.

Ripley and MP/GA



(a) MP/CL - 26+29 nodes (b) MP/GA - 2+2 nodes (c) MP/GA - 3+3 nodes

Figure 4: Hiperboxes created by MP/CL and MP/GA together with the training data.

Ripley and MP/GA

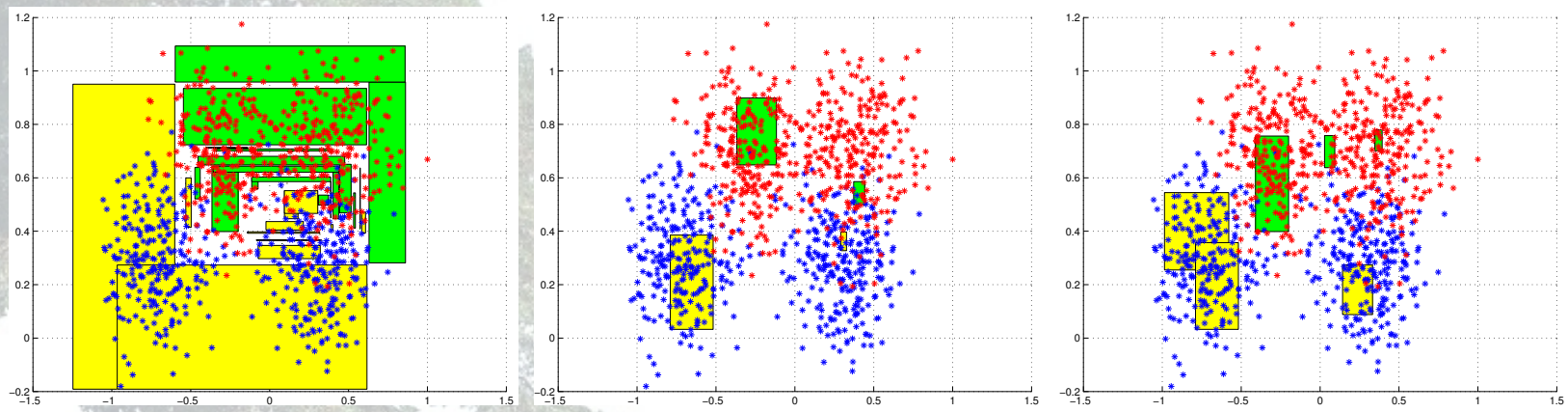


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Figure 5: Hiperboxes created by MP/CL and MP/GA together with the testing data.

Concluding Remarks

Conclusions

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