Self-organizing acoustic categories in sensor arrays

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Abstract. In this paper, we explore the emergence of acoustic categories in sensor arrays. We describe a series experiments on the automatic categorization of species and individual birds using self-organizing maps. Experimental results showed that meaningful acoustic categories can arise as self-organizing processes in sensor arrays. In addition, we discuss how distributed categorization could be used for the emergence of symbolic communication in these platforms.

1 introduction

Sensor arrays are finding use in an increasing variety of applications. This technology holds the potential to produce a major paradigm shift in the way we interact with the physical environment (Estrin et al, 2001). Enabling sensor arrays with adaptation capabilities would be a major step towards realizing the full potential of this emerging technology.

We envision sensor arrays as collections of intelligent agents that behave as a single ensemble. In this idealization, agents can recognize concepts and discourse intelligently about them. The realization of these capabilities relies crucially on the ability to categorize data, to ground symbols into perceptual categories and to propagate symbols in a community of other agents. In effect, each sensor node needs to categorize their experiences, to bind categories with symbols and communicate to other nodes using a collection of mutually intelligible symbols. Previous studies have established plausible scenarios for the emergence of these capabilities in sensor arrays (Collier and Taylor, 2005; Friedlander and Phoha, 2002).

Conversely, sensor arrays are excellent platforms for studying fundamental topics on artificial life research, such as emergence and self-organization. In effect, organisms may be viewed as collections of sensors, actuators and processors of limited abilities, communicating primarily with other sensors, actuators and processors that are mostly at their immediate neighborhood, and mostly with limited bandwidth, functioning together as an ensemble (Taylor, 2002).

A fundamental aspect of living systems is their categorization capabilities (Pfeifer and Bongard, 2007). Furthermore, the remarkable ability to distinguish among different elements in the environment is crucial for the viability of an organism. However, usefulness of categorization is often contingent to the creation of meaningful categories. We believe sensor arrays are appropriate testbeds for exploring these issues on animal cognition.

In this work, we conducted a series of experiments on the emergence of acoustic categories in sensor arrays. We describe a series of experiments in which self-organizing maps are used to automatically create categories on species of birds and individual birds in an ecological monitoring application. Experimental results showed that meaningful categories can arise as self-organizing processes in sensor arrays.

2 The model

In this section, we propose a formal framework for conducting computational experiments in sensor arrays. We first provide a series of definitions and then describe an implementation of this model based on self-organizing maps.

The formal definitions presented below are based on considerations of the models proposed in (Vallejo and Taylor, 2004) and (Zhao and Guibas, 2004).

2.1 Definitions

A sensor array is a distributed collection of interconnected sensor nodes. Such an array is described by the underlying graph and a set of properties related to both the sensor nodes and the links.

Formally, a sensor array is a 4-tuple:

$$G = \{V, E, P_V, P_E\}$$

where:

1. V is a set of nodes
2. $E \subseteq V \times V$ is a set of links
3. P_V is a set of functions related to properties of V
4. P_E is a set of functions related to properties of E

A sensor node consists of a collection of sensors. A node can ground categories to features in the flood of perceptions that come into its sensors. A node also has the capability for symbolic communication with other nodes via the transmission and the reception of a set of symbols.

Formally, a sensor node is an 8-tuple:

$$v = \{P, X, C, S, \delta, \phi, \tau, \psi\}$$

where:

1. P is finite set of sensors
2. X is set of input vectors
3. C is a finite set of perceptual categories
4. S is a finite set of symbols
5. $\delta : \rho(P) \to X$ is the perception function
6. $\phi : X \to C$ is the categorization function
7. $\tau : C \to S$ is the transmission function
8. $\psi : S \to C$ is the reception function

A sender node v_1 comunicates to a receiver node v_2 in a sensor array as follows. Initially, v_1 perceives an input vector from the environment and associates this input with a perceptual category. Then, v_1 relates the category with a symbol and transmits the symbol to a node v_2. Node v_2 receives the symbol and interprets it as a category. The communication is successful if both the categories of the sender and the receiver match.

Formally, $v_1 = \{P_1, X_1, C_1, S_1, \delta_1, \phi_1, \tau_1, \psi_1\}$ communicates successfully to $v_2 = \{P_2, X_2, C_2, S_2, \delta_2, \phi_2, \tau_2, \psi_2\}$ given an input vector $\mathbf{x} \in X$ if the following conditions are satisfied:

1. $\phi_1(\mathbf{x}) = c_i$
2. $\tau_1(c_i) = s_i$
3. $\psi_2(s_i) = c_j$
4. $c_i = c_j$

Finally, we consider several assumptions that are often present in sensor arrays: (1) each sensor node communications only to its neighbors, (2) communication is by broadcast to these neighbors, and (3) node layout follows an arbitrary, but fixed topology.

3 Experiments and results

3.1 Experiment 1: categorization of bird species

In this experiment, we explore the emergence of acoustic categories describing bird species from their songs. We used bird songs recorded at the Montes Azules Biosphere Reserve in Chiapas, Mexico. From these recordings, we constructed a training set consisting of 15 spectral and temporal features of the acoustic signal for the simulations reported here as shown in table 1.

An unsupervised competitive learning neural network was used to implement the categorization function ϕ in the nodes of the sensor array. A competitive network consists of a single layer of output units c_i, each fully connected to a set of inputs o_j via excitatory connections w_{ij} (Kohonen, 1997).

Given an input vector $\mathbf{o}$, the winner is the unit c_{i^*} with the weight vector $\mathbf{w_{i^*}}$ as follows:

$$|\mathbf{w}_{i^*} - \mathbf{o}| \leq |\mathbf{w}_i - \mathbf{o}| \text{ (for all } i)$$

Bird species	Samples
Dusky antbird (DAS)	65
Barred antshrike (BAS)	127
Great antshrike (GAS)	123
Mexican antthrush (MAT)	114

Table 1. Bird species data set

After each training step, the sensor node updates the weights w_{i^*j} for the winning category c_{i^*} only, as follows:

$$\Delta w_{i^*j} = \eta(o_j - w_{i^*j})$$

where $\eta \in [0, 1]$ is the learning constant.

Multiple simulations were conducted using different combinations of parameter values as shown in table 2. Simple competitive neural networks correctly identified four categories in the data set. In addition, the accuracy of unsupervised classification on this data set was 76–86.7%.

Parameter	Value
Categories	4–10
Learning rate	0.001–0.005
Simulation steps	500

Table 2. Parameters for the simulations

Self-organizing maps were also used for unsupervised categorization. Figure 1 shows the obtained results. Dark areas represent clusters of similar elements in the data set. The left part of the figure is the U-matrix (i.e. Unified Distance Matrix). The U-matrix shows the results of the unsupervised classification obtained by the SOM. In this figure dark areas are interpreted as clusters and light areas as cluster boundaries. The right part of the figure represents actual values associated to each cell. This representation may be viewed as the supervised classification used by the SOM to evaluate the obtained results. There exists some overlap between BAS and GAS as these species possess similar song repertoires. This can be appreciated in the self-organizing map as well as in the principal components graph shown in figure 2.

3.2 Experiment 2: categorization of MAT individuals

In this experiment, we explore the emergence of acoustic categories describing MAT individuals from their songs. We used recordings from the same field site as before. From these recordings, we constructed a collection of training and

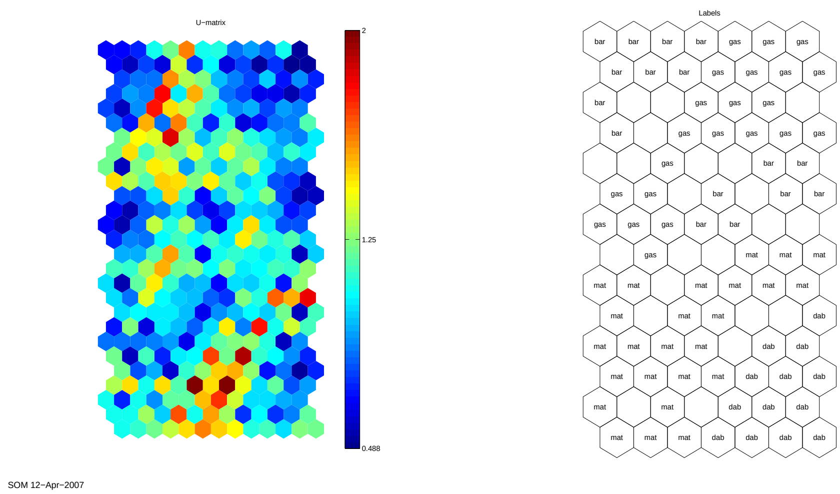

Fig. 1. Self-organizing maps: species.

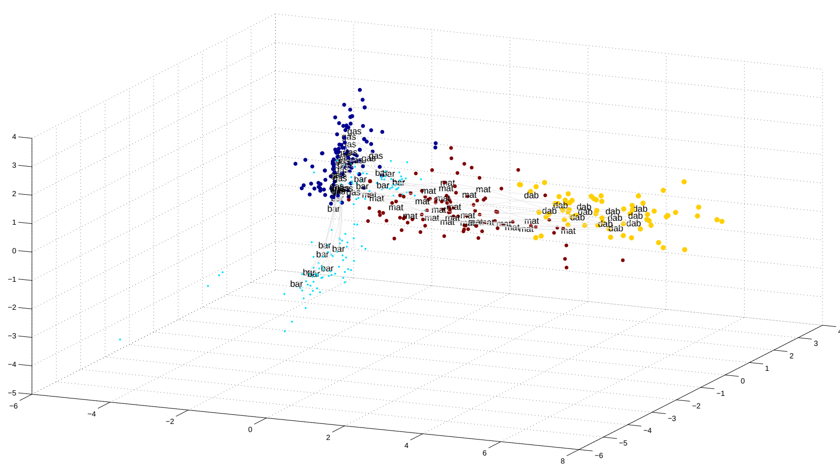

Fig. 2. Self-organizing maps: three principal components

validation sets consisting of 5 spectral and temporal features of the acoustic signal for the simulations as shown in table 3.

MAT individual ID	**Samples**
PMPa	28
PMPb	21
LGEa	12
PBEa	25
AVEa	38
AVEb	5
LCNa	4
LCNb	18
SNWa	17
SNWb	3

Table 3. Birdsong data set

We conducted multiple simulations as before. Simple competitive neural networks fail to correctly identify the categories in the data set. More precisely, the accuracy of unsupervised classification was 52–56%.

Figure 3 shows the results obtained using self-organizing maps. It can be appreciated that unsupervised neural networks were unable to accurately identify the underlying individuals in the data set.

We conducted additional experiments using Learning Vector Quantization (LVQ1) (Kohonen, 1997). LVQ is the supervised version of competitive learning. The MAT individuals was partitioned into 60% training, 20%validation and 20% test sets.

After each training step, LVQ updates eights w_{i^*j} for the winning category c_{i^*} only, as follows:

$$\Delta w_{i^*j} = \begin{cases} +\eta(o_j - w_{i^*j}) \text{ if category is correct} \\ -\eta(o_j - w_{i^*j}) \text{ if category is incorrect} \end{cases}$$

Multiple simulations were conducted as before. The accuracy of supervised classification for MAT individuals was 90.17–97.65%. Figure 4 shows the training results using a learning rate value of 0.001 and 0.005, respectively. It can be appreciated that training should be stopped after about 100 epochs to avoid overfitting of the training set.

3.3 Emergence of symbolic communication in sensor arrays

Self-organizing maps locally induce categorization at sensor nodes. This form of categorization does not imply a shared collection of categories among the nodes in the array. In general, different nodes can associate a perception with

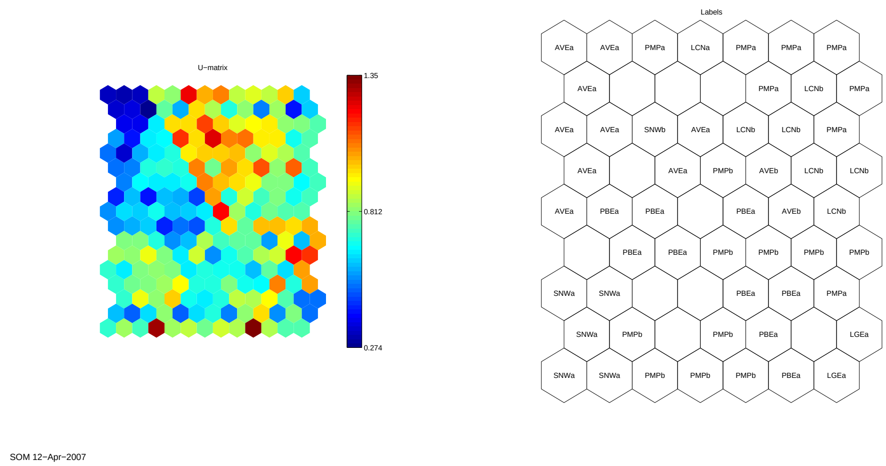

Fig. 3. Self organizing maps: MAT individuals.

different categories. Sensor nodes may be in a position to perceive correlations between perceptions and categories from other nodes. This can provide the basis for properly identify the appropriate category for a particular input.

For example, figure 5 shows two different self-organizing maps obtained from two mutually exclusive partitions from the species data set. The obtained self-organizing maps shows some overlap in the dark areas, so they could be in a position to communicate and understand to each other, given that the same symbol is used to describe the same category.

Therefore, once categorization has been achieved at the nodes of the sensor array, they could supervise to each other using a language game in order to arrive to a collection of shared symbols (Steels, 2003; Arita and Taylor, 1996).

4 Discussion

Despite its preliminary character, the results shown here seem to indicate that meaningful categorization can emerge as self-organizing processes in sensor arrays. Furthermore, symbolic communication holds the potential for reducing the bandwith requirements for sensor arrays. However, it appears that the capabilities of self-organizing maps to perform automatic categorization will be severely constrained by the complexity of the perceptions, so complementary approaches should be considered (e. g. supervised learning, information theory).

It should be noted that the proposed model has only been tested in a simple simulated setting. We will test the categorization and generalization capabilities of the proposed model in real settings in the near future. Other applications of

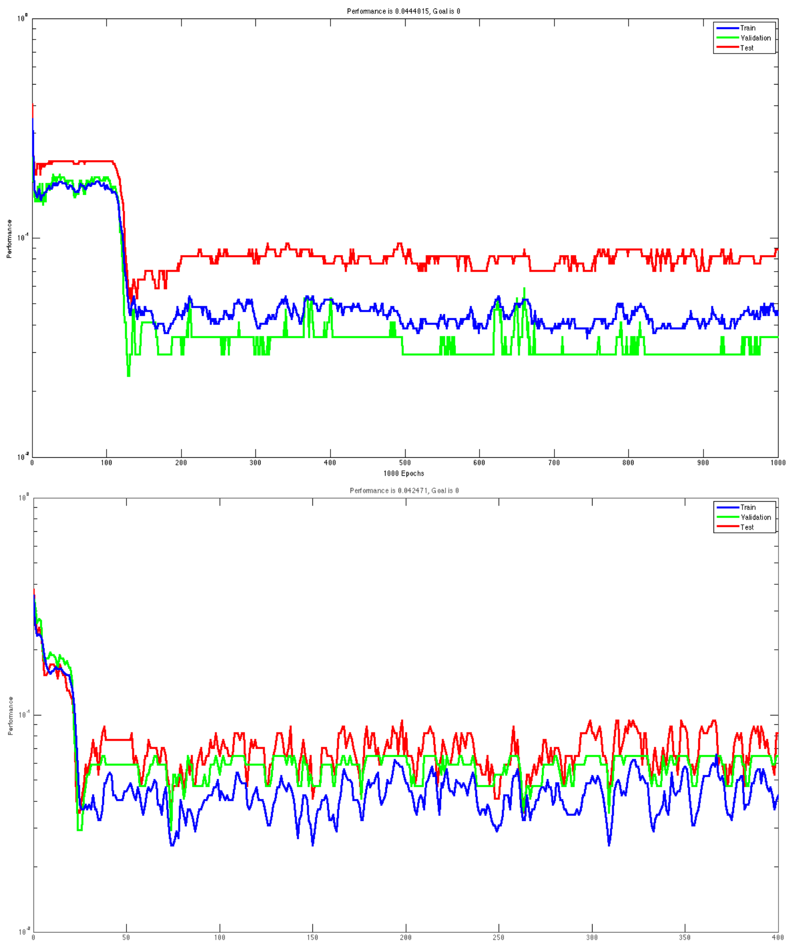

Fig. 4. Learning vector quantization: categorization results

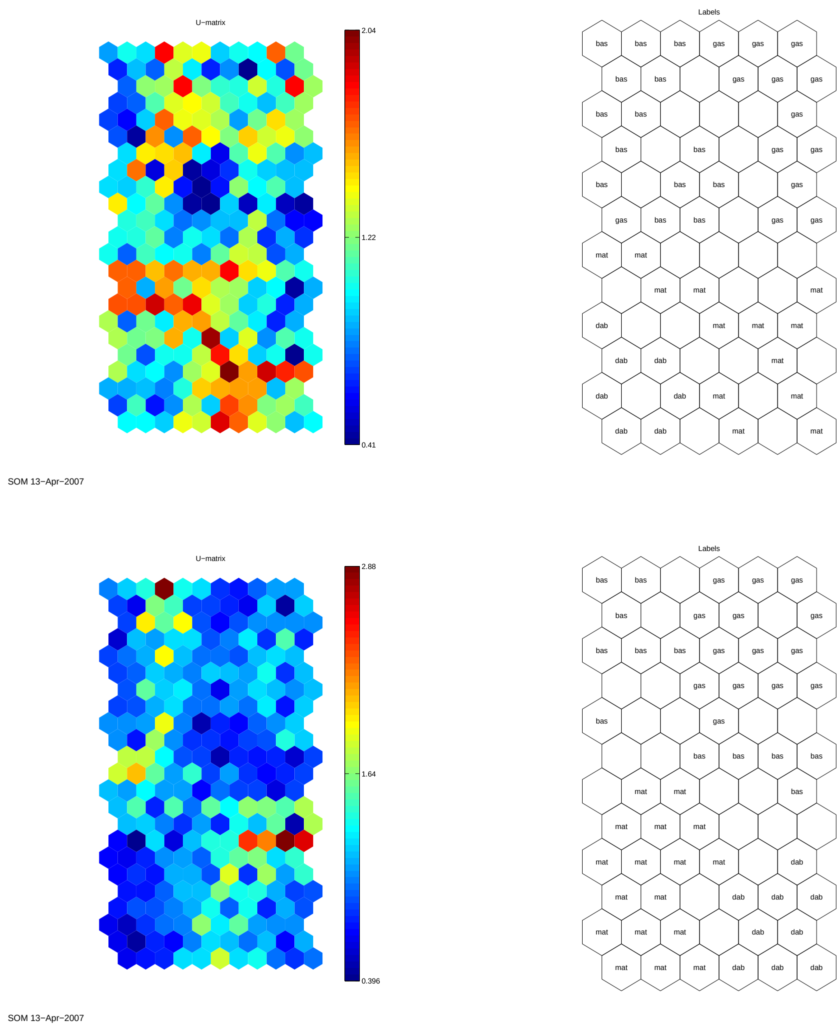

Fig. 5. Self-organizing maps two partitions of the data set

sensor arrays such as localization and tracking would contribute to the understanding of the potentials of competitive learning neural networks for automatic categorization in sensor arrays.

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