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# Multi-criteria self-organization: Example of motor-dependent phonetic representation for a multi-modal robot

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## Abstract

This paper presents a computational self-organizing model of multi-modal information, inspired from cortical maps. It shows how the organization in a map can be influenced by the same process occurring in other maps. We illustrate this approach on a phonetic - motor association, that shows that the organization of words can integrate motor constraints, as observed in humans.

## 1 Introduction

In the evolutionary process, the appearance of the cerebral cortex had dramatic consequences on the abilities of mammals, which reach their maximum in humans. Whereas it can be said that the limbic system added an emotional dimension on purely reactive schemes [16], the cerebral cortex offers a new substratum devoted to multimodal information representation [3]. When one considers the associated cost of this neuronal structure in terms of energy needs and size in the limited skull, it can be thought that the corresponding functions might be complex but highly interesting from an adap-

tive point of view.

Basically, the cerebral cortex is often described as a set of topological maps representing sensory or motor information, but also merging various representations in so-called associative maps. Concerning afferent connections toward cortical maps, the topological principle explains that information coming from sensors is represented along important dimensions, like retinotopy for the visual case. Moreover, at a lower level of description, some kind of filtering process allows to extract and represent onto the mapping other functional informations [2], like orientation selectivity or color contrast in the visual case.

Concerning cortico-cortical connections, the important role of these internal links must be underlined. For example, the cerebral cortex and the cerebellum are reported as having approximately the same number of synapses ( $10^{12}$ ) [8] and the big difference of volume between these structures can be explained by the fact that internal connections are much more numerous in the cerebral cortex (more than 75%). These internal connections inside the cerebral cortex are observed as belonging to a map, to achieve the topological representation, but also

as connecting maps, which is fundamental to create associative maps [13, 3].

From a functional point of view, the role of the cerebral cortex has often been described as unsupervised learning [5]. In the statistical domain, the goal of unsupervised models like the K-means, hierarchical classification, Principal Component Analysis (PCA), Independent Component Analysis (ICA) is to categorize information from the regularities observed in its distribution (as opposed to an external signal, seen as a teacher or a supervisor) or to select in a high dimensional space the most interesting axes on which to project information. It must be underlined that such information processing is very consistent with the cortical organizational principles of topological representation and filtering.

From a modeling point of view, neuronal models are among the most well-known unsupervised techniques. The central one is certainly Kohonen's Self-Organizing Map [10], which has been proposed from its origin as a model of a cortical map and has been applied in various sensory domains (cf. for example [11] for the visual case, [9] for the auditory case, etc.). Later, from this simple but powerful scheme, other more complicated models have been elaborated to fit more closely to the biological reality (cf. for example [15] for the visual case), but they all rely on the same fundamental principle of competitive learning, as observed in the cerebral cortex.

Interestingly, it must be noticed that most of these neuronal models lay emphasis on the representation of one sensory or motor information and not on the joint organization of several interacting flows of information. Nevertheless, several data from neurosciences indicate that this function is also present in cortical processing. To tell it differ-

ently, the cortex is not only several self-organizing maps, each one representing its own modality (or set of modalities in the associative case) and communicating one with the other, but rather a set of maps acting all together to represent information of the external world from different but cooperating points of view in a global way.

Of course, such a holistic view cannot be obtained if, as it is often the case, one unique map is considered in the modeling process. The fact is that several biological data indicates that the cortical processing cannot be only summarized by independent self-organizations.

From a connectivity point of view, we have indicated above the important role which is given to recurrent cortico-cortical connections. This might be consistent with asking for a global consistency in representations on top of simple local competitions. Several electrophysiological studies have shown that a cortical region can change the kind of information it represents in case of a lesion (e.g. changing representation of the finger in a lesioned monkey [17]) or in case of sensory substitution (e.g. tactile stimulation for blind people [19]).

From a representational point of view, several brain imaging studies [14] have shown that word encoding within the brain is not only organized around phonetic codes but is also organized around action.

How this is done within the brain has not yet been fully explained but we would like to present how these action based representations naturally emerge in our model by virtue of solving constraints coming from motor maps.

## 2 Model features

The model features are presented briefly in the following sections. A more detailed presentation can be found in [12], where the current model is applied to a simplified version of a target reaching problem with an artificial arm.

### 2.1 Maps, units and competition

The main computational block of the model is a set of computational units called a map. A map is a sheet made of a tiling of identical units. This sheet has been implemented as a disk, for architectural reasons described further. When input information is given to the map, each unit shows a level of activity, depending on the similarity of the information it receives with the information it specifically detects, as will be detailed in section 2.2. That activity, noted  $A^t$ , follows a Gaussian *tuning curve* in the model:  $A^t$  is a matching activity, that is maximal if input information exactly corresponds to the *prototype* of the unit, and gets weaker as input gets different from this prototype.

When an input is given to the map, the distribution of matching activities among units is a scattered pattern, because tuning curves are not sharp, which allows many units to have non null activities, even if prototypes don't perfectly match the input. From this activity distribution over the map, a small compact set of units that contains the most active units has to be selected. Unlike in SOMs where this decision is made by a centralized "winner-take-all" process, decision is made here by a numerical distributed process, emerging from a local competitive mechanism, as in [4].

In order to decide which units are lo-

cally the best matching ones inside a map, a local competition mechanism is implemented. It is inspired from theoretical results of the continuum neural field theory (CNFT) [1, 18], but it is adapted to become independent of the number of connections, thus avoiding disastrous border effects : the CNFT algorithm tends to choose more often units that have more connections. Thus, the local connection pattern within the maps must be torical, with units in one border of the map connected to the opposite border. Here, the field of units in the map computes a distribution of global activities  $A^*$ , from current matching activity  $A^t$  distribution independently of the position of units within the map.

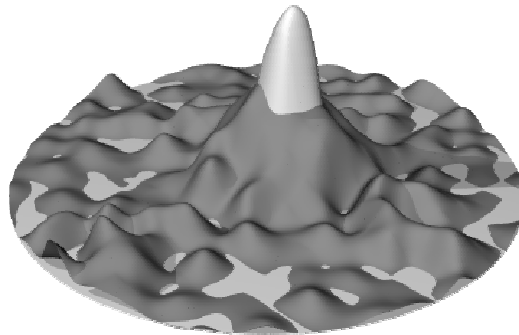


Figure 1: Result of competition in a map among the  $A^t$  (dark gray) and resulting  $A^*$  (light gray). A bubble of  $A^*$  appears where  $A^t$  is the strongest in its neighborhood.

The result of this competition is the rising of a bubble of  $A^*$  activity in the map at places where  $A^t$  activities are the most significant (cf. figure 1). The purpose of the resulting  $A^*$  activity is twofold. First, this activity defines the main activity of the unit : This activity is the one that is viewed by other connected units in all activation rules detailed further. Second, all learning processes are modulated by this activity. That means that only units in  $A^*$  activity bubbles

learn in the map.

The global behavior of the map, involving an adaptive matching process, and a learning rule dependent on a competition, reminds the Kohonen SOM. However, the local competition algorithm used here allows to feed the units with different inputs. The source of information received by a unit differs from one unit to its neighbors, because of the stripe connectivity described below in section 2.3. Another difference with SOM not previously detailed is that, in our model, competition and learning are not separated stages. Learning is dependent on  $A^*$ , and also occurs during the  $A^*$  bubble setting.

## 2.2 Matching activity computation

It has been mentioned previously that competition is computed on the basis of a matching activity  $A^t$ . As detailed below, this activity is actually the merging of several matching results, and it may be considered as a global matching activity. Inside the units in the model, each matching result is performed by a computational module called a layer. Therefore, a layer in our model is a subpart of a unit, computing a specific matching, and not a layer of neurons as classically reported in various models. It is inspired from the biological model of the cortical column by [7]. A layer gathers inputs from the same origin (a map), and computes a matching value from the configuration of these inputs. As a consequence, the behavior of a unit can be described as the gathering of several layers. These are detailed in the following.

First of all, some maps receive input from the external world. Each unit in the map reacts according to the fitting of this input to a preferred input. In the cortex,

the thalamus plays a role in sending inputs to the cortex. In our model, the layer which tunes a preferred perception is called a thalamic layer. This layer provides a thalamic matching activity. We extend this terminology for motor maps.

One other kind of layer is the cortical layer. It receives information from another map. The connectivity of this layer will be further discussed in section 2.3. Let us just say for now that its purpose is to compute a cortical matching activity that corresponds to the detection of some  $A^*$  activity distribution in the remote units it is connected to.

If the map is connected to a number  $n$  of other maps, its units have  $n$  cortical layers, thus computing  $n$  cortical matching results (one per cortical layer). These matchings are merged to form a global cortical matching. If the map has a thalamic layer, the thalamic matching result is then merged to the global cortical matching, to form the global matching  $A^t$  the competition is performed on.

To sum up, our model stresses the two kinds of cortico-cortical connections mentioned in section 1. The maps compute activity bubbles, that are a decision enhancing the most relevant units from local connections belonging to the map. This decision depends on external input, computed by the thalamic layer, but also on the state of other maps through cortical layers, that implement long range cortico-cortical connections. This computation is a multi-criteria decision, that has complex dynamics, since it performs a competition from input, but also from the competition that is performed in the same way in other maps. One consequence of this dynamics, central to the model, is that the self-organization in a map is modulated by the organization in the other maps, as illustrated in section 3.

## 2.3 Inter-map stripe connectivity and disk-shaped maps

A cortical layer, that receives information from another map, doesn't receive inputs from all the units of the remote map, but only from one stripe of units (cf. fig. 2). For instance, a map may be connected row-to-row to another map : each unit in any row of the first map is connected to every remote units in the corresponding row of the other map. These connections are always reciprocal in the model.

This limited connectivity is biologically grounded, as cortical zones are connected to other zones by stripes [3, 2]. Moreover, it has a computational purpose : If inter-map connectivity were total (if each unit in a map were connected to every unit in a connected remote map), the number of connections would rise too quickly as the size and the number of the maps increase and would lead to a combinatorial explosion. Since this model has been designed to handle multiple sensorimotor connections, the risk is real and map-to-map connectivity has to be limited.

A stripe has an orientation that is specific to a map-to-map connection : a map that is connected to many other ones has a different direction of connection for each kind of connection. In order to keep the model homogeneous, the shape of the map must not favor any direction. This is the reason why the maps are disk-shaped in our model.

Two analogous cortical layers of two neighboring units are connected to parallel, adjacent and overlapping stripes in the remote map. Neighboring units receive close but not identical inputs. That is why a winner-takes-all algorithm over the whole map isn't suitable, as already explained.

Through the inter-map connectivity, our model produces *resonance* between connected maps: Activity patches in connected maps can only stabilize within connected modular stripes. The role of reciprocally connected stripes is crucial for this resonance. As activity  $A^t$  is the basis for inner-map lateral competition (computation of  $A^*$ ), and as this  $A^t$  depends on some cortical activity(ies), computed from other cortical inputs, bubbles of  $A^*$  activities raise in the maps so that the following property is satisfied: The bubble of activity that appears in an associative map is at the intersection of the stripes where activity bubbles coming from the connected maps stand.

In our model, this matching of activity can be compared with a phenomenon of resonance, as described in the ART paradigm by Grossberg [6], that produces stable and coherent states across the different maps. It ensures consistency of the activity bubbles across two connected cortical maps. Since units learning rate is modulated by their  $A^*$ , units whose  $A^*$  are activated simultaneously in the different maps learn together. We call this *coherent learning*. Learning strengthens the connection between these coherent units, so that they will tend to activate together again in the future.

## 2.4 Activation and learning rules

As mentioned before, cortical and thalamic layers of the units in the model have to perform a tuning from the input they receive, so that all matchings are merged to constitute the global matching activity  $A^t$ . This merging concerns all cortical and thalamic layers, and is computed from a geometric mean. This must be seen as a tricky way to compute some kind of numerical AND operator. Know-

ing these merging principles, let the computation of each elementary matching, and their associated learning rule, be detailed for both thalamic and cortical layers.

The thalamic layer in the model behaves similarly to neurons in Kohonen maps. This is a custom defined point in the model, depending on the actual entry format received by the map. For example, thalamic tuned activation can be a decreasing function of a well suited distance between the input and a prototype. Then learning consists of making the thalamic prototype be closer to the current input. This learning process has to be modulated by  $A^*$  activity for thalamic layer to be coherent with the remaining of the model. This is also what is done in Kohonen maps, where learning rate depends on a decreasing function of the proximity of a neuron with the winning one. This decreasing function in Kohonen algorithm is analogous to the  $A^*$  bubble of activity in the model.

The cortical layers all use the same matching and learning rules. Each cortical activity is computed from a cortical prototype pattern and the cortical input pattern, which is actually the  $A^*$  activity distribution in the connected stripe of remote units. The layer matching activity has to be high only when both the  $A^*$  of a remote unit and the corresponding value in the prototype are high: the cortical layer detects that a remote unit to which it is highly connected is active, and thus performs a computational “AND”. The learning rule is a Hebbian/anti-Hebbian rule. It is, as for the thalamic layer, modulated by  $A^*$ .

A unit learns only when it actively participates in the recognition process, i.e. when it is at a place where a  $A^*$  bubble stands. It learns both its thalamic and cortical prototypes, which creates

and then maintains coherence between the different layers. The full unit model is summarized in figure 2.

## 2.5 Joint-organization

To conclude on the model behavior, the combination of self-organization and coherent learning produces what we call *joint organization*: competition, although locally computed, occurs not only inside any given map, but across all maps. Moreover, the use of connection stripes limits the connectivity, which avoids the combinatorial explosion that would occur if the model were to employ full connectivity between the maps. Thus, coherent learning leads to both efficient data representation in each map and coordination between all connected maps.

## 3 Model behavior on a simplified example

### 3.1 The phonetic-action association problem

Several brain imaging studies [14] have shown that word encoding within the brain is not only organized around purely phonetic codes but is also organized around action. How this is done within the brain has not yet been fully explained but we would like to present how these action based representations naturally emerge in our model by virtue of solving constraints coming from motor maps.

We therefore applied our model to a simple word-action association. A part of the word set from the European MirrorBot project, which is a 3 year EU-IST-FET project, was used in a “phonetic” map, and we tried to associate

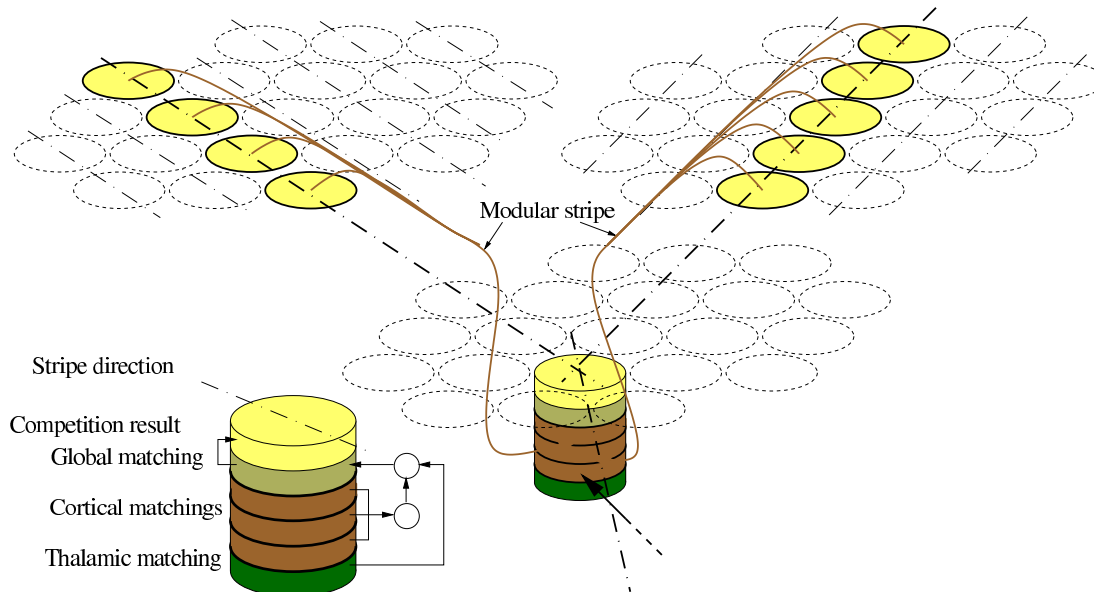


Figure 2: Full functional scheme : The cortical matching activities, obtained from the modular stripe inter-map connections, are merged together. The thalamic matching is merged with the result to form a global matching activity. This activity is then used in the competition process described in section 2.1

these words to the body part that performs the corresponding action. One goal of this project is to define multimodal robotic experiments and the corresponding protocols are consequently well suited for this task.

### 3.2 Phonetic and motor coding

The phonetic coding used in our model is taken from the MirrorBot project. A word is separated into its constituting phonemes. Each phoneme is then coded by a binary vector of length 20. Since the longest word we use has 4 phonemes, each word is coded by 4 phonemes, and if they have less, they are completed by empty phonemes.

The distance between two different phonemes is the Cartesian distance between the coding vectors. The distance between two words is the sum of the distances between their constituting

phonemes. While we are well aware that this is a very naive way to represent the phonetic distance between two words, it is sufficient in order to exhibit the joint organization properties discussed in this paper.

The actions are coded in the same way as the words : there are 3 different input actions (head action, body action and hand action), and each action is coded as a binary vector of length 3. The distance between two actions is, once again, the Cartesian distance between their representing vectors.

Each word is semantically associated to a specific action. The word-action relationship is shown on figure 3.

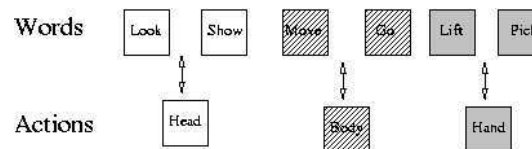


Figure 3: Word-action relationship



The thalamic prototypes (i.e. external inputs) of the motor and the phonetic units are, respectively, coded actions and coded words. However, these do not necessarily correspond to real input words or actions : these prototypes are vector of float values, not binary ones. The prototype of a unit, in the figures of this section, is represented as the nearest “real” input, in term of the distance previously discussed.

### 3.3 Interest of associative learning

Our model fundamentally differs from a classical Kohonen map since this latter one is somehow topologically organizing information against the sole notion of distance between inputs and prototypes. Thus if we were to use a Kohonen map to represent words from the MirrorBot grammar (encoded as a phonetic sequence), a consequence of the Kohonen algorithm and existing lateral interaction between units would be an organization toward similarity relation of word codes only (i.e. two words having similar code would be represented by the same prototype or neighbor prototypes) as illustrated in figure 4. This kind of representation is not satisfactory in the sense that it is totally disconnected from other maps and does not take any semantics of words into account.

### 3.4 Emergence of action oriented representation

Let us consider three maps, one for word representation, one for action representation and finally an associative one that links word to action (cf. figure 5).

The central point of our model is that coherent learning within a map depends on some other maps, so that the inter-

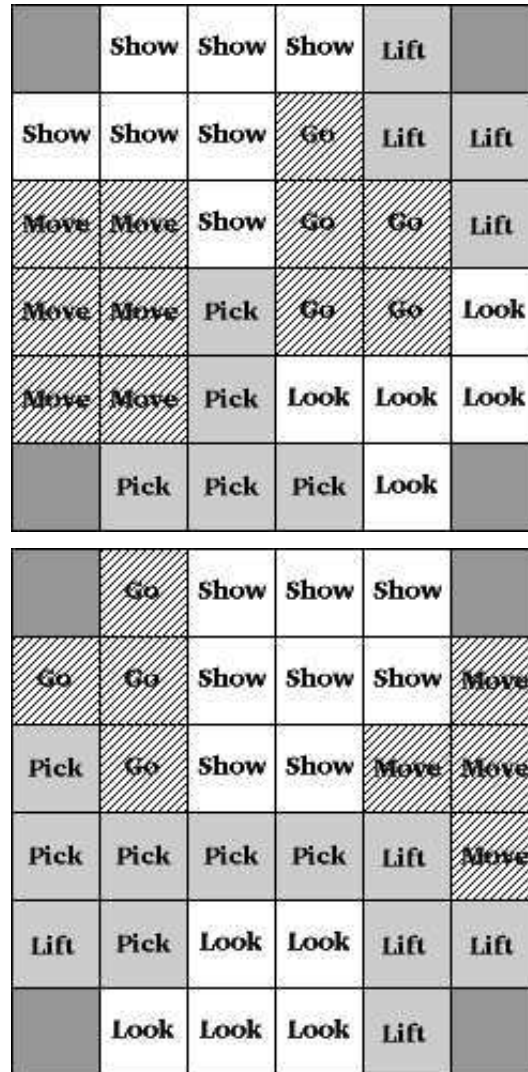


Figure 4: Two different results of word classification by a Kohonen map based on purely phonetic representations. Words representing eye action (white), hand action (gray) or body action (stripes) are spread all over the map without paying any attention to the underlying semantic of words.

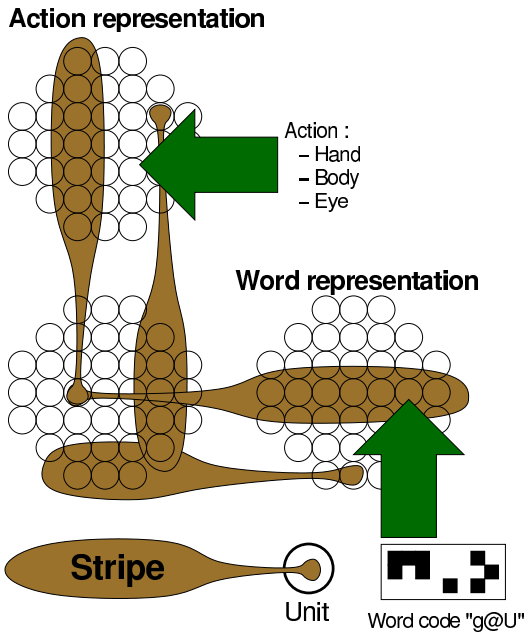


Figure 5: Schematic view of the model architecture: the word representations and the action representations are presented in separate maps, that are both connected to an associative map by reciprocal cortical connection stripes.

map connectivity biases the convergence to a particular self-organized state, when self-organization alone would have allowed for many more possible ones. The final state of organization in each map must allow the bubbles to be set up at intersecting cortical connection stripes. The cortical maps perform an effective compromise between the local and remote constraints. Remote constraints, coming from the architecture, makes activity bubbles have strong cortical connections to each other. Local constraints, coming from the thalamic layers, requires bubbles of activity to raise where the phonetic or action prototypes best match the phonetic or action input. This compromise is poor at the beginning, but it gets better as learning proceeds.

In the current word-action association, we have chosen to impose a frozen organization to the action map, in order to illus-

trate how the phonetic map self-organizes when keeping coherence with the action map. As an illustration, let us consider the words “look” and “show”. The phonetic representations of these words are completely different, so that a Kohonen map classifies them in different parts of the map (cf. fig. 4). In our model, however, the higher level associative map linking auditory representation with motor action will use close units to represent these words, since they both relate to the same action (head action). As our model deals with an implicit global coherence, it is able to reflect this higher level of association and to overcome the simpler phonetic organization.

The interesting point to consider here is that word representations (e.g. phonetic map) are constrained by some topology that mimics to some extent physical properties of effectors, i.e. a word unit is dedicated to one action (e.g. hand) and cannot trigger another one (e.g. head). In order to solve this constraint and to ensure a global coherence, the model must then organize word representation in such a way that, for example, any body word should be linked to a body action.

As illustrated in figure 6, we can clearly see that the topological organization found by the model meets these criteria. Within the word map, words are grouped relatively to the body part they represent: body action words are grouped together (stripes) as well as hand action words (gray) and head action words (white).

However, the phonetic distribution of words remains the most important factor in the phonetic map organization. Each word is represented by a “cluster” of close units, and the words whose phonetic representation is close tend to be represented in close clusters of units. For instance,

|      |      |      |      |      |      |
|------|------|------|------|------|------|
|      | Look | Look | Show | Show |      |
| Lift | Look | Look | Go   | Go   | Show |
| Look | Move | Move | Go   | Show | Show |
| Show | Move | Move | Go   | Show | Show |
| Move | Look | Lift | Lift | Pick | Pick |
|      | Go   | Look | Lift | Pick |      |

|      |      |      |      |      |    |
|------|------|------|------|------|----|
|      | Pick | Look | Look | Look |    |
| Look | Pick | Pick | Look | Look | Go |
| Pick | Pick | Pick | Show | Show | Go |
| Lift | Lift | Pick | Show | Show | Go |
| Lift | Lift | Move | Move | Move | Go |
|      | Lift | Move | Move | Move |    |

Figure 6: Two simulation results of word representation map after coherent learning has occurred with our model. Word representations are now constrained by the motor map via the associative map and, as a result, words that correspond to the same action are grouped together. Nevertheless, phonetic proximity is still kept.

while *Go* and *Show* correspond to different motor actions, their phonetic representations are close, so that their representing clusters are adjacent (cf. fig. 6). This illustrates the fact that the model is actually doing a successful compromise between the local demands, which tend to organize the words phonetically, and the motor demands, which tend to put together the words that correspond to the same action. The joint organization does not destroy the local self-organization, but rather modulates it so that it becomes *coherent* with the other map organization.

Finally, having this model based on the self-organization of information prototypes leads implicitly to an organization that can be interpreted since it is easy to see what a unit is tuned on. This might be useful for further qualitative comparisons with real fMRI activations.

## 4 Discussion

The model presented in this paper is designed for a general cortically-inspired associative learning. It is based on the cooperation of several self-organizing maps, that are connected one with the other. The design of this model stresses some computational points, that keeps the model functionally close to the biology. The first one is locality, since each unit computes its status from the units it is connected to, without any superior managing process. This leads to the set up of a distributed competition mechanism, whose emerging effect is the rise of a bubble of activity at locally relevant places in the map. The second computational point the model stresses is stripe connectivity between maps. From a strictly computational point of view, this keeps the number of connections under combinatorial explosion. Moreover, the conse-

quent computation has more interesting properties. Using stripes actually constrains the model to overcome partial connectivity by organizing the maps so that related information stands at connected places. This is supported by resonance between cortical layers, and leads to organize states in each map according to the organization of the maps it is connected to. This dependency isn't explicitly given to the model, it can be viewed as a side effect of the shortage of connections. This effect has been observed in our previous work [12] concerning the arm guidance, but it wasn't of primary importance in that context.

However, in the present paper, the property of joint organization the model exhibits is reported in the framework of semantic coding observed in cortical areas, since high level word representation appears to be organized according to the body part the word refers to. The ability of our model to generate such kind of organization without any supplementary specification supports its relevance as a functional model of cortical computation, in spite of sometimes less plausible computational mechanisms that keeps the model tractable for a large amount of units.

Considering self-organization of many interconnected self-organizing modules leads to discuss the organization of representations at a global level, that may appear rather more abstract than the organization resulting from the mapping of a mono-modal distribution, as performed by usual unsupervised learning techniques. In the context of autonomous robotics, that this model addresses, anything that is learned is obviously a situated representation. Moreover, the model makes the organization of a particular module in the architecture, dealing with one specific modality, be under-

standable according to the other modules, and more generally according to the global purpose of such an architecture to address situated behavior. This raises the hypothesis that the influence of the global behavioral purpose at the level of each modality representation is the very property that endows this representation with a semantic value. Therefore, this view of semantics, inspired from biological facts about cortical areas involved in language, appears to be tractable by a joint organizing model, and to be more generally suitable for any situated multimodal processing in robotics.

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