Learning Control Units

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1 Introduction

Rapid self-organization of a mapping between two patterns plays an important role in various visual tasks, such as object recognition, stereo matching and motion estimation. This task is difficult because of the variations we have to deal with, among which shift, scale, orientation and noise. Dynamic Link Matching (DLM) [1] is a matching process that is ideal in dealing with many of the variations, but it is too slow to account for the split-second recognition times in adults.

We previously presented an extension to DLM that has significantly shorter convergence time[2, 3]. The extension is based on *synaptic control units*, each of which stands for a group of synapses that are consistent with each other in terms of transformation parameters. Control units and their connections represent stored knowledge of transformations that leads to the speedup of DLM: significant local patterns can be retrieved by control units and be propagated rapidly through the interconnections between control units.

But previously the control units and the connections between them were all designed manually. This becomes very difficult if the deforming patterns become complicated. Therefore we present here a model to learn control units and the connection between them from examples.

2 Learning rules

Both control units and their connections are learned by generalized Hebbian plasticity. For conceptual simplicity, we view control units as real neurons that have receptive fields (RFs), so learning control units means learning their RFs.

Examples used for learning are consistent mappings formed, for example, by slow conventional DLM. Each mapping is represented by a synaptic matrix $x(r,t)$, where r is the position in one pattern (image domain) and t the other (model domain).

RFs are localized in space. This is done by dividing the synaptic matrix into small regions, indexed by s, with membership function $A_s(r,t)$. Different regions can overlap with each other. For each s there is a set of control units, with RFs $K_{si}(r,t)$. The response of unit $K_{si}(r,t)$ to input $x(r,t)$ is:

$$y_{si} = \sum_{r,t} x(r,t) A_s(r,t) K_{si}(r,t).$$

For each input mapping $x(r,t)$, the learning rule for RFs is:

$$\triangle K_{si}(r,t) = \alpha A_s(r,t) x(r,t) y^*_{si}, \tag{1}$$

where

$$y^*_{si} = \begin{cases} y_{si} & \text{if } argmax_j(y_{sj}) = i \\ 0 & \text{otherwise} \end{cases}$$

and α is the learning rate.

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In order to avoid uncontrolled growth, this update is followed by a normalization:

$$\sum_{r,t} K_{si}(r,t) = \text{const.} \tag{2}$$

The connection between control units K_{si} and $K_{s'i'}$, $c(s,i,s',i')$, is also learned by Hebbian rule:

$$\triangle c(s,i,s',i') = \beta y_{si} y_{s'i'}, \tag{3}$$

where β is the learning rate. This is also followed by normalization:

$$\sum_{s'} \sum_{j \neq i} c(s,i,s',j) = \text{const.} \tag{4}$$

Initially the RFs are set to random numbers, and the interconnections between them are 0. Then, for each input learning case, the system updates according to the above learning rules.

3 Simulations

The development of control units and their connections is simulated in an example in which the goal is to learn shift invariance for 1D patterns. Each learning case is a mapping between a pair of relatively shifted, but otherwise identical, image and model. Accordingly the synaptic matrix has value 1 along a diagonal, and 0 elsewhere. The position of the diagonal corresponds to the shift parameter, which is generated randomly and uniformly over all possible shifts. Noise in the mapping is simulated by randomly setting elements next to the diagonal value 1. In the simulation, the synaptic matrix is of size 20*20, and is divided into 4*4 small regions, each of which has size 5*5. In each small region there are 9 control units. Learning cases are presented sequentially, and for each input example, the control unit RFs and their connections are updated according to equations (1) and (3), respectively, with normalization. We use normalization constant= 1, and $\alpha = \beta = 0.1$.

As a result, the learned RFs resemble those designed by hand previously. We can see visually that control units which share the same RF center have different shift parameters. They often span the whole range of possible shifts. But we also noticed that even after 1000 training examples, it is still possible to have few uncommitted slots, i.e., control units with unstructured RFs. They could be used for other variations such as scale.

The learned interconnections between units are checked by reconstruction: for any control unit indexed by si, compute the summation of RFs of all control units, weighted by their connection strength to unit si: $\sum_{s',i'} c(s,i,s',i') A_{s'}(r,t) K_{s'i'}(r,t)$. In most instances, the reconstructed result resembles one of the training examples, i.e., a diagonal line, meaning that all control units with the same shift are connected, while those with different shift are not.

We also did simulations on learning simultaneously shift and scale invariance for 1D patterns. The results are very encouraging.

4 Discussion

This work demonstrates the feasibility to learn control units and their connections. The learning rules will be the same for 2D patterns. This learning illustrates the general problem of representing and developing compound features, which our brains solved ingeniously.

Future work includes using these learned results to replace the hand crafted ones in the previous model.

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References

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