Learning Control Units for Invariant Recognition

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Introduction

Rapid self-organization of a mapping between two patterns plays an important role in various visual tasks such as object recognition. This task is difficult because of the variations we have to deal with, such as shift, scale and orientation. 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 time 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 represent stored knowledge that can be retrieved and propagated rapidly, leading to the speedup of DLM.

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.

Learning rules

Both control units and their connections can be 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 $A_s(r,t)$. For each s there is a set of control units, with RFs $K_{si}(r,t)$. The connection between control units K_{si} and $K_{s'i'}$ is $c(s,i,s',i')$. The response of unit $K_{si}(r,t)$ to input $x(r,t)$ is

$$y_{si} = \sum_{r,t} x(r,t)A_s(r,t)K_{si}(r,t) + \sum_{s',i'} c(s,i,s',i')y_{s'i'}.$$

Initially the RFs are set to random numbers, and the interconnections between them are 0. In learning, for each input mapping $x(r,t)$, the learning rule for RFs is:

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

followed by a normalization:

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

where $y^*_{si} = y_{si}$ if $argmax_j(y_{sj}) = i$, and 0 otherwise. α is the learning rate.

$c(s,i,s',i')$ is also learned by a quasi-Hebbian rule:

$$\triangle c(s,i,s',i') = \beta y^*_{si} y^*_{s'i'},$$

followed by normalization:

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

where β is the learning rate.

Results and Discussion

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. The results are very encouraging. The RFs learned resemble those designed by hand. The interconnections between units are also correct, as shown by reconstruction.

This work demonstrates the feasibility to learn control units and their connections. The same learning rules apply to other invariances and to 2D patterns. We are working on learning simultaneously multiple invariances, such as shift and scale. Eventually these learned results will replace the hand crafted ones in the previous model.

References

[1] L. Wiskott and C. von der Malsburg, Face Recognition by Dynamic Link Matching, in *Lateral Interactions in the Cortex: Structure and Function*,Electronic book, 1996.

[2] J. Zhu and C. von der Malsburg, Fast Dynamic Link Matching, *ICCNS*01*, 2001.

[3] J. Zhu and C. von der Malsburg, Synapto-Synaptic Interactions speed up Dynamic Link Matching, *CNS*01*, 2001.