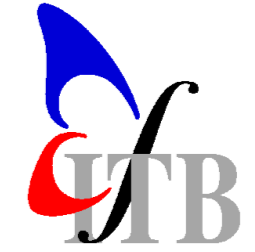
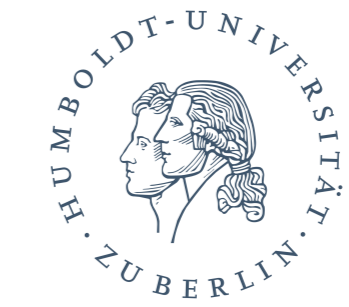


# Hierarchical Slow Feature Analysis and Top-Down Processes



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## Abstract

Top-down processes are thought to play an important role in the mammalian visual system, e.g., for interpreting ambiguous stimuli. Slow Feature Analysis (SFA) [4] on the other hand is proven to be an efficient algorithm for the bottom-up processing of visual stimuli [1, 2, 3]. Therefore it seems natural to combine bottom-up SFA with top-down processes. One major obstacle for this is the quadratic expansion step in our model. While we had limited success with top-down image reconstruction it seems that more fundamental changes are needed to solve the problems.

## Hierarchical Visual Model

### Slow Feature Analysis (SFA)

Behaviorally relevant features of our environment generally change on a much slower timescale than the raw visual data. This inspired the slowness learning principle which has been turned into a well defined optimization problem [4] (fig 1.a):

Given a function space  $\mathcal{F}$  and a multi-dimensional input signal  $\mathbf{x}(t)$  find a set of instantaneous functions  $g_j(\mathbf{x}) \in \mathcal{F}$  such that the output signals  $y_j(t) := g_j(\mathbf{x}(t))$

$$\text{minimize } \Delta(y_j) := \langle \dot{y}_j^2 \rangle_t$$

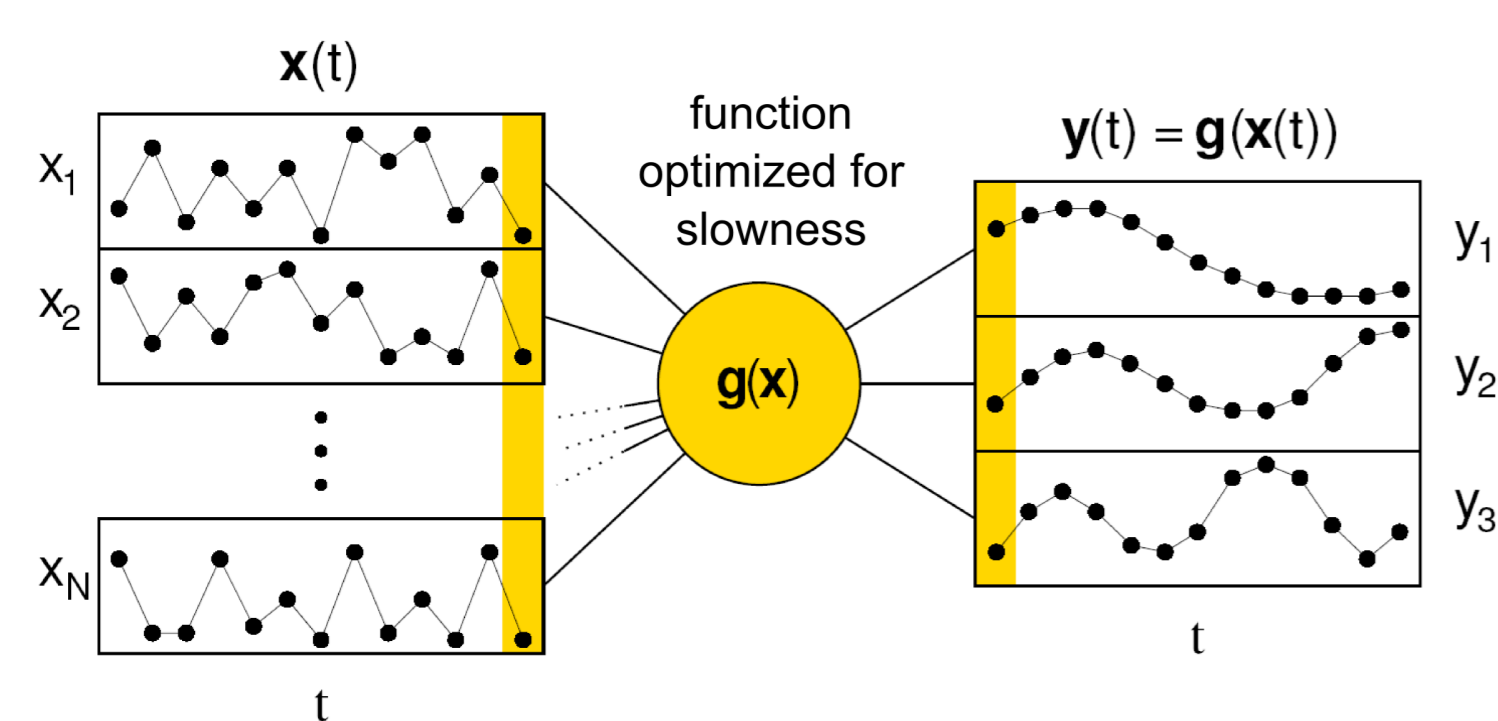
under the constraints

$$\begin{aligned} \langle y_j \rangle_t &= 0 \quad (\text{zero mean}), \\ \langle y_j^2 \rangle_t &= 1 \quad (\text{unit variance}), \\ \forall i < j : \langle y_i y_j \rangle_t &= 0 \quad (\text{decorrelation and order}). \end{aligned}$$

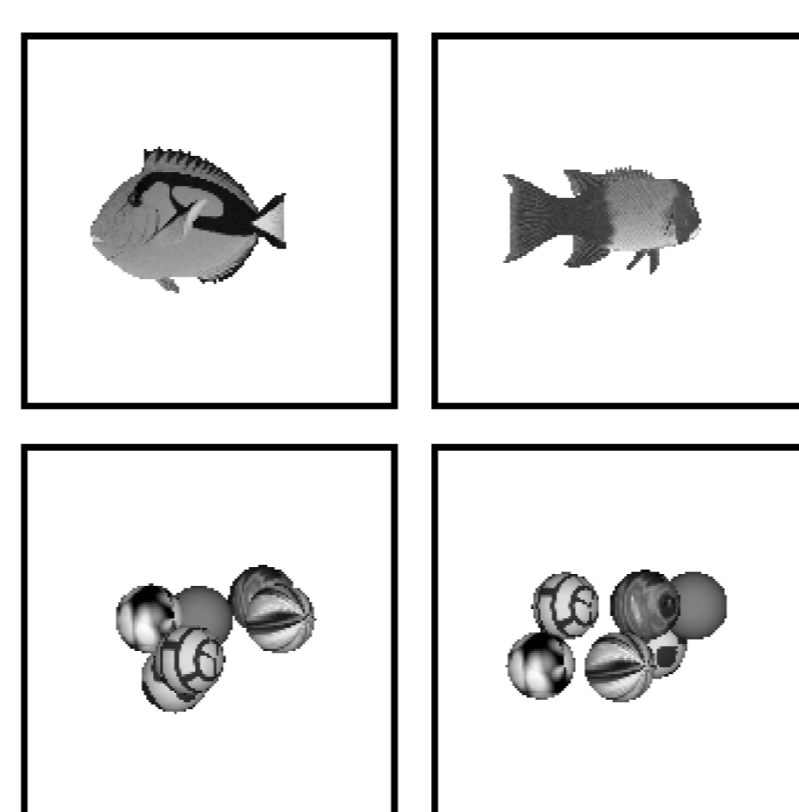
### Invariant Object Recognition

We train a hierarchical feed-forward model for invariant object recognition [2] (fig 1.c). Each network layer is based on the SFA algorithm and includes quadratic expansion.

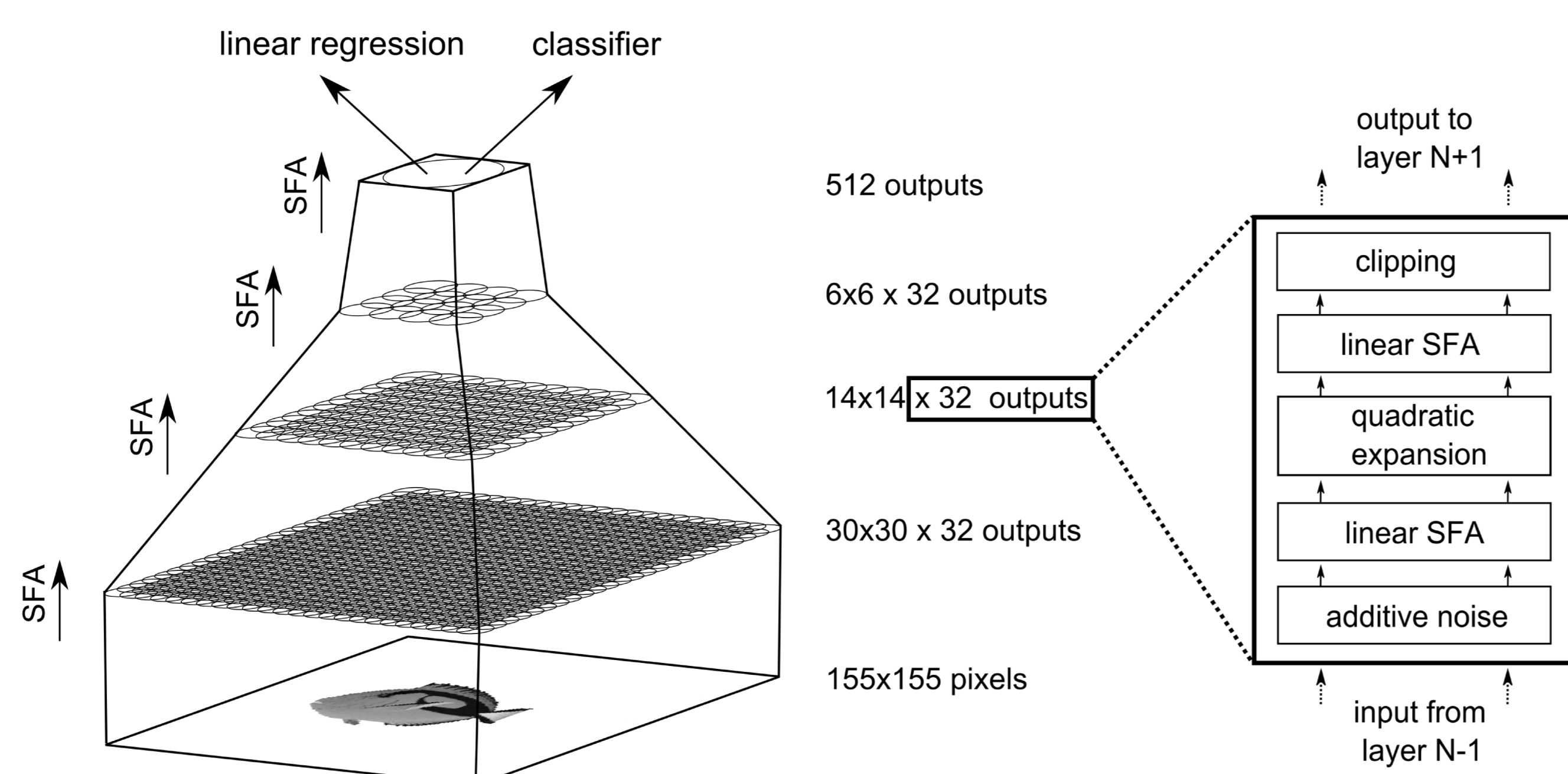
#### 1.a Slow Feature Analysis



#### 1.b Model Input Examples



#### 1.c Architecture of the Hierarchical Model based on SFA



Most of the model software is now part of the “Modular Toolkit for Data Processing” (MDP) open source project [5].

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## Top-Down Image Reconstruction

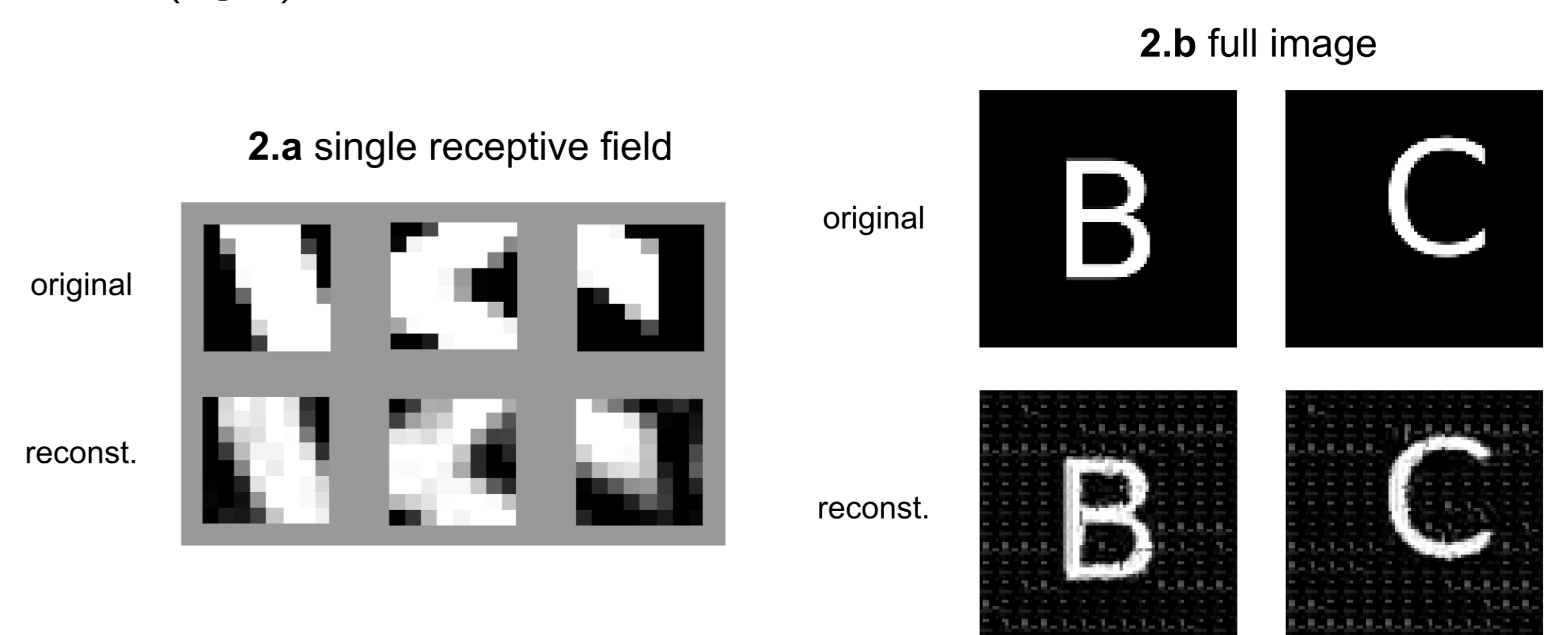
Due to the quadratic expansion there is no clear correspondence between the individual input and output components of a layer. As a first step towards resolving this issue we looked at the reconstruction problem: For a given output find a corresponding input that is similar to the training data.

We combined the following techniques:

- Gradient descent to minimize the quadratic error of the layer output.
- Vector quantization to capture the distribution of the training set, providing starting points for the gradient descent.
- Winner-take-all for overlapping receptive fields (based on the error).

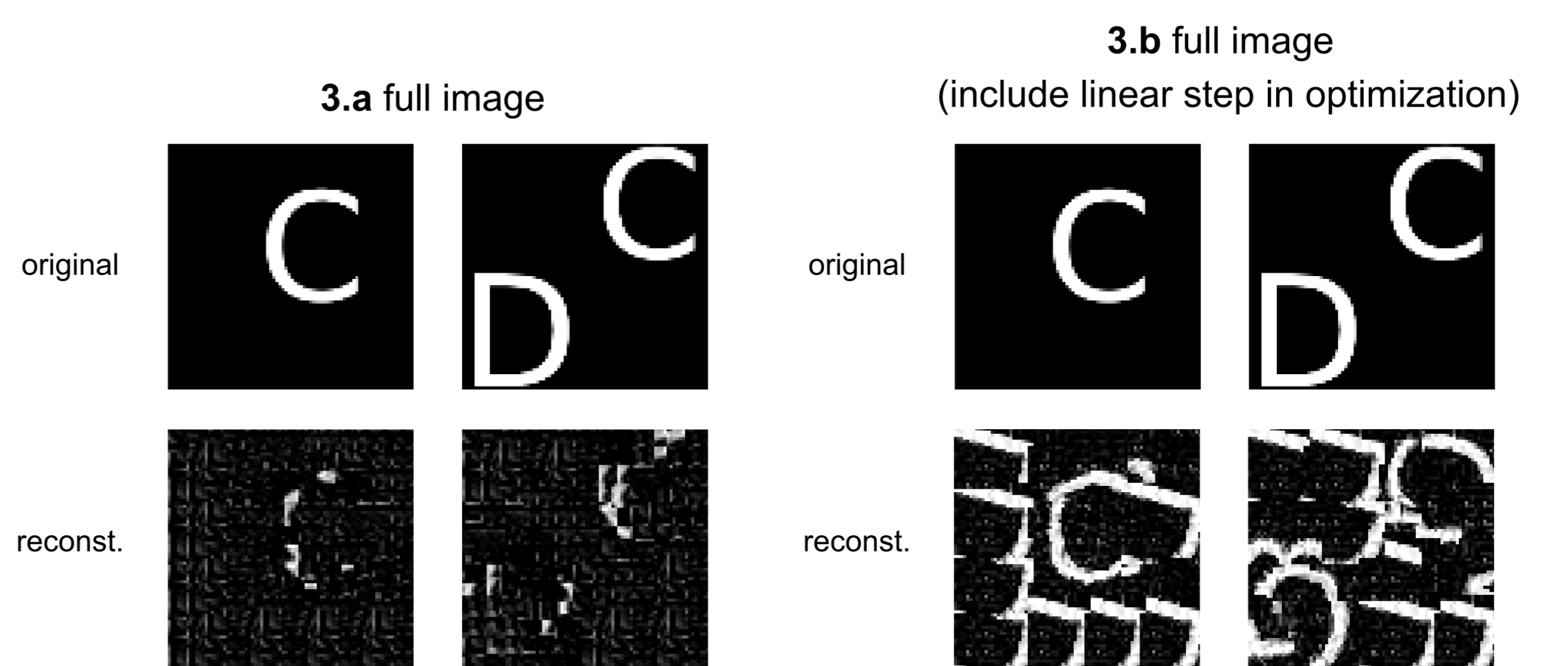
### First Layer Reconstruction

The optimization for the lowest layer works reasonably well for synthetic stimuli (fig 2).



### Second Layer Reconstruction

On the second layer the reconstruction result is severely degraded (fig 3).



At the third layer no sensible reconstruction was possible.

## Conclusion

We conclude that our model is currently not able to adequately address top-down processes, due to the following problems:

- The quadratic polynomial function space leads to many local minima in the error function. In practise this is a huge problem, which is not solved by the vector quantisation or any other technique we tried.
- The overlap of the receptive fields does lead to conflicts, which are not adequately resolved at higher layers by the winner-take-all approach.

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