

Co-development of Visual Receptive Fields and Their Motor Primitive-based Decoding Scheme

Huei-Fang Yang and Yoonsuck Choe
Department of Computer Science
Texas A&M University
College Station, TX 77843-3112
Email: hfyang@cs.tamu.edu, choe@tamu.edu

Abstract—Neurons in the primary visual cortex respond to specific patterns of visual input, i.e., the spikes encode visual feature properties. These patterns define the receptive field of the neurons. Receptive fields are known to become refined over time throughout development, and the process has been intensively studied both by neurophysiological and computational methods. The focus of these earlier studies has been on the representational properties relating to natural image statistics and information theoretic concerns. Only recently researchers started to raise questions about how subsequent stages of visual processing can utilize the response of the primary visual cortical neurons. In our previous work, we proposed a model based on reinforcement learning to allow subsequent stages discover the encoded feature properties in visual cortical spikes, through the use of motor primitives. However, in that model, the receptive fields had a fixed pattern. In this paper, we will extend our previous model to include receptive field development. In contrast to approaches based on statistical properties of images alone, we propose that receptive field development should take into account the motor component. We present a model which uses the Hebbian learning rule to develop receptive fields and reinforcement learning to link the visual cortical spikes to meaningful motor primitives. Our results suggest that receptive field development is strongly influenced by the motor system, and also that visual receptive fields and the sensorimotor mapping (that helps decode the spikes) can develop simultaneously. We expect the conceptual framework presented here to facilitate deeper understanding about biological vision and about the precise role played by action.

I. INTRODUCTION

Neurons in the primary visual cortex respond to specific patterns of visual input. These patterns define the receptive field of the neurons (see [1] for a review). Thus, in some sense, the neurons “encode” visual features resembling their receptive fields.

How these encodings are learned has been intensively studied, both in neuroscience experiments [2]–[4] and in computational models [1], [5]–[11]. The focus of these earlier studies has been on the representational properties relating to natural image statistics and information theoretic concerns. Fig. 1 shows examples of learned receptive fields.

Only recently researchers started to raise questions about how subsequent stages of visual processing can utilize the response of the primary visual cortical neurons. For example, Salinas showed that functional requirements of downstream (motor) neurons determine the response property of early

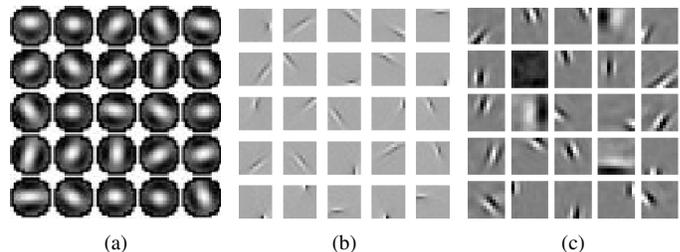


Fig. 1. **Development of Receptive Fields.** Learned receptive fields from (a) Miiikkulainen et al. [1] (b) Bell and Sejnowski [7] and (c) Olshausen and Field [6] are shown. The shape of the receptive fields (mostly Gabor-like) largely derive from the statistical properties of natural images. Note that only parts of the original figures are shown.

sensory neurons [12], and Sejnowski proposed that we should look at the “projective fields” as well as receptive fields [13].

In our previous work, we proposed a model based on reinforcement learning to allow subsequent stages discover the encoded feature properties in visual cortical spikes (i.e., “decode” the spikes, or semantically ground the representations), through the use of motor primitives [14]–[17]. However, in that model, the receptive fields had fixed oriented Gabor patterns. In this paper, we will extend our previous model to include receptive field development. Unlike approaches based on statistical properties of images alone, we propose that receptive field development should take into account the motor component.

There are other works where learning of receptive fields are modulated by the motor system [18], [19], but the role (or goal) of the motor component was unclear. It is apparent that the involvement of the motor system will inevitably bias the statistical properties of the received input [20], and that will lead to differentiation in structure and function of the visual cortex [1], [5].

The real question however is, is there anything beyond that? In our case, the goal of such motor engagement is clear: autonomous semantic grounding of internal brain states. We present a model which uses (1) the Hebbian learning rule to develop receptive fields and (2) reinforcement learning to link the visual cortical spikes to meaningful motor primitives. Our results suggest that receptive field development is strongly influenced by the motor system (confirming results by other

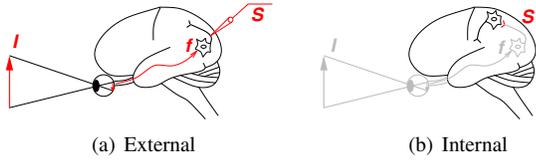


Fig. 2. **External vs. Internal Observer.** (a) External observers (e.g., scientists observing a brain) have full access to both the environmental stimulus and the spikes. By correlating the spikes to the input, the stimulus properties carried by the spikes can be inferred. (b) Internal observers (e.g., downstream neurons) have access to the upstream neuron’s spikes only, making such an inference seem impossible. Adapted from [15], [16].

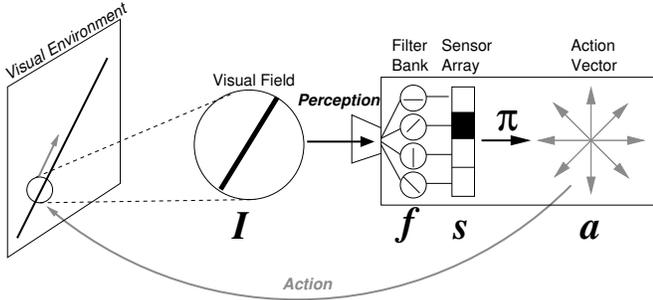


Fig. 3. **A Visuomotor Agent.** The agent has a limited field view and a set of sensory primitives f . Sensory primitives f receive input and generate an activity in the sensory array s . Adapted from [15], [16].

researchers), and, more importantly, that visual receptive fields and the sensorimotor mapping that helps decode the spikes can develop simultaneously.

The remainder of the paper is organized as follows. First, we will begin with some background. The next section describes the details of our model and the learning rules, followed by experiments and results. Then we will discuss important issues relating to our work, and finally conclude the paper.

II. BACKGROUND AND MOTIVATION

For a natural agent to behave in a meaningful way, it needs to understand the properties of the external stimulus environment. However, how does an agent, which cannot directly access the external world but only its internal state (i.e., brain state) learn the basic properties of the external world? That is, how can the agent decode its internal state, based on the internal state only? For example, consider Fig. 2. External observers (e.g., scientists) have access to both the external input and the internal states of the brain under observation (Fig. 2(a)), so we can infer what properties are encoded by the internal state. However the brain can only access the internal state of itself (Fig. 2(b)), so the approach taken by the external observer is not applicable. We showed that this problem can be solved through the use of action (Fig. 3) that fulfills a simple criterion of internal state invariance (Fig. 4) [16].

Consider a simple agent shown in Fig. 3, with limited visual field view and a set of sensory receptive fields. Neurons with sensory receptive fields (shown as oriented lines) receive input and generate activities in the sensory array s (modeling the visual cortex). Based on the activity of the sensory array,

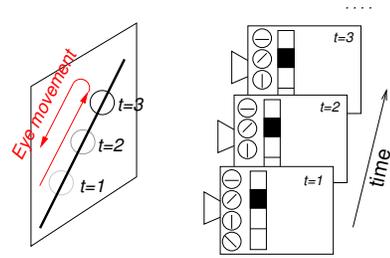


Fig. 4. **Invariance in Internal State during Motion.** The agent moving in diagonal direction (45° or 135° in this example) will keep the internal state unchanged. By generating a behavior congruent with input stimulus, the agent can infer external world from internal state. Adapted from [15], [16].

motor response (eye movement) can be generated. This can be modeled as a mapping π . How can this added capability to move the gaze help in decoding (or grounding, [21]) the internal state (the spikes in the visual cortex)? Our main observation was that the meaning of the spikes can be recovered through a specific kind of eye movement. Take the state of the agent shown in Fig. 4 for example. At time $t = 1$, the input activates the neuron tuned to 45° input. (Note that the agent has access to the neuron’s spikes.) Suppose the agent happened to move in the 45° direction and back (135°). The result would be that the internal state does not change over time ($t = 1, t = 2, t = 3$, on the right) even though the agent is generating motion. The key observation here is that (1) the property of such a motion and (2) the stimulus property represented by the spike are identical. In converse, if the agent had the goal of moving while maintaining its internal state invariant over time, it will end up generating action that reflects the property of the encoded spike. This way, the internal state can be decoded (grounded), all without direct access to the external world. Thus, internal state invariance can serve as a strong criterion for grounding internal representations.

However, the above picture does not take into account the fact that receptive fields are not fixed and given from the beginning. Further, for an agent residing in a specific environment, its sensory receptive fields should reflect the statistics of the external stimulus space. Below, we will investigate if receptive field development and the learning of grounding can proceed simultaneously, and how.

III. METHODS

In this section, we will describe how to process the input image, generate sensory activities, learn the mapping from the sensory states to motor primitives, and adapt sensory receptive fields.

A. Initial input processing

Below, we follow the steps described in our earlier work [16], so we will only provide a sketch of the overall process. Please refer to [16] for details. The whole process is summarized in Fig. 5, from left to right. First, the raw input image I_R (640×480) is convolved by a Difference of Gaussian (DoG). The DoG filter was 15×15 in size, with the width parameter σ set to $15/4$. The resulting image was normalized to have

zero mean and the max range scaled down between -1.0 and 1.0. This resulted in the convolved image I_D . From this image a small 9×9 are was sampled, resulting in the input I .

B. Response generation

The cortical response generation process is outlined in Fig. 5. Given a set of receptive fields the vectorized dotproduct between the input sample I and the receptive fields G_i are calculated, resulting in the response vector \mathbf{r} . (In the figure, eight oriented Gabor filters are shown, but these can be an arbitrary pattern, as it may have to be adapted throughout development.) The vector \mathbf{r} is then normalized by its l_2 -norm $\|\mathbf{r}\|$. The current state index s is determined by:

$$s = \arg \max_{\theta=1..n} r_i, \quad (1)$$

where θ is the index of the receptive field, and n the number of receptive fields.

C. Learning

Learning in the agent model occurs in two different parts: (1) internal state to action mapping ϕ , and (2) receptive field structure. Learning of ϕ follows closely our previous work [16], so again, we will just provide a brief overview rather than going into details. The agent's gaze is controlled by a stochastic process based on the conditional probability $P(a|s)$ where $a \in A$ is the gaze direction and $s \in S$ is the internal state indicating the maximally responding unit in the sensory array. Given a specific current state s , action a is chosen with the probability $P(a|s)$. The task is to learn this conditional probability so that when the above scheme is employed, maximum state-to-state invariance is achieved over time. For convenience, let us write $R(s, a)$ (and call it the reward table) instead of $P(a|s)$, in the following (see Fig. 6).

$R(s, a)$ is basically trained using a reinforcement learning algorithm. The degree of invariance serves as the reward (ρ), and it is simply defined as the dotproduct of successive response vectors at time $t - 1$ and t : $\rho_t = \mathbf{r}_t \cdot \mathbf{r}_{t-1}$. $R(s, a)$ is updated as:

$$R_t(s_{t-1}, a_{t-1}) = R_{t-1}(s_{t-1}, a_{t-1}) + \alpha \rho_t \quad (2)$$

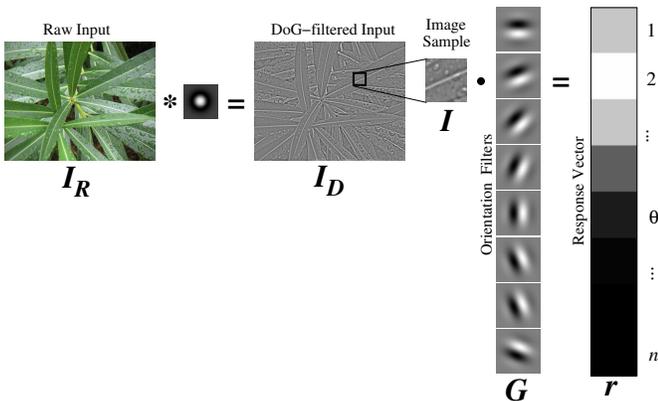


Fig. 5. **Response Generation.** An overview of the response generation process is shown. See text for details.

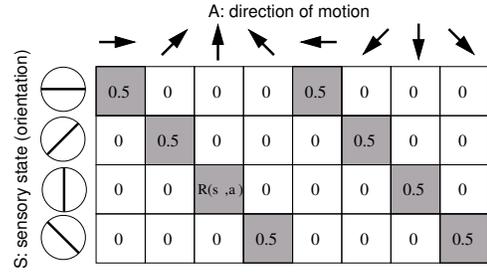


Fig. 6. **Reinforcement Learning of Internal State to Action Mapping.** The rows represent the internal sensory state (orientation in this case), and the columns the direction of motion (gaze). For each orientation, in an ideal case, there are two optimal directions to move to maintain invariance in the internal state. For example, for 0° orientation, one can either move left or right. Thus, the reward table $R(s, a)$ has a diagonal structure as shown above, in an ideal case. Adapted from [15], [16].

where $R_t(\cdot, \cdot)$ is the reward table at time t and α the learning rate (set to 0.002 typically). Then, $R_t(s_{t-1}, a)$ values are normalized by their sum for all $a \in A$.

The agent not only learns the mapping from receptive fields to motor primitives but also adapts its receptive fields at the same time. We used a normalized Hebbian learning rule to adapt the receptive fields:

$$g_{ij} = \frac{g_{ij} + \alpha(I_{ij} - g_{ij})}{\sum_{mn} g_{mn} + \alpha(I_{mn} - g_{mn})}, \quad (3)$$

where g_{ij} is a weight of the receptive field and I_{ij} the input at location (i, j) , and α the learning rate. Note that the α was set to a positive value starting from 0.05. For the receptive field with the highest response, it exponentially decreased over time and set to a negative value starting from 0.005, and for all others, it exponentially decreased over time. Furthermore, receptive fields were trained only when the correlation in previous and current response vectors were above a certain level (typically 0.2), taking into account the invariance criterion.

IV. EXPERIMENTS AND RESULTS

In order to assess the influence of motor factors in receptive field learning, and to investigate whether receptive field development and internal-state-to-action mapping can be learned simultaneously, we conducted two experiments.

In the first experiment, we compared the development of receptive fields under two different, fixed, internal-state-to-action mappings: (1) random reward table (Fig. 7(a)), and (2) ideal reward table (Fig. 7(b)). Again, these reward tables were fixed throughout the learning trial. With this, we could measure the effects of motor policy on receptive field learning. In this experiment, we trained 8 receptive fields on the natural image shown in Fig. 5. The agent was trained for 70,000 iterations with a learning rate of 0.005. Fig. 7 shows that with random motor policy, the receptive fields are formed slowly and malformed (second and the last column), and the order is random whereas with ideal $R(s, a)$ motor policy, the receptive fields are formed quickly and more importantly the order reflect the motor primitives. Thus, the property of the motor

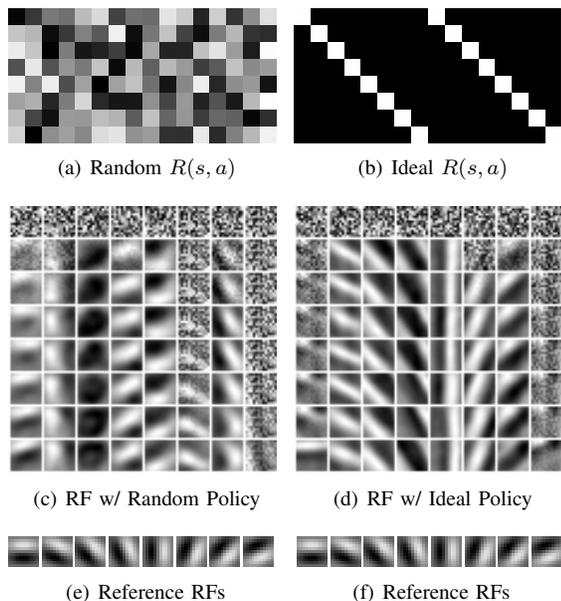


Fig. 7. **Learned receptive fields (RFs) using fixed policies.** (a, b) The fixed reward tables; (c, d) the learned receptive fields over time, from top to bottom; and (e, f) reference receptive fields (plain Gabor filters) are shown. In all plots, black represents min and white max. The receptive fields trained with a random policy has malformed receptive fields (second and last column), which is not the case for those trained with the ideal policy.

primitives (“downstream requirement”) dictates the receptive field property (cf. [12]).

In the second experiment, we allowed both the receptive fields and the reward table to learn at the same time. The agent was given 16 sensory receptive fields and thus had 32 corresponding motor primitives, and trained for 100,000 iterations, with other conditions identical to those in Sec. III. Fig. 8 shows the learned receptive fields over time from top to bottom, and the final $R(s, a)$ values. The receptive fields learned reasonably well, but the reward table $R(s, a)$ looks totally disorganized. However, this is simply because the ordering of receptive fields do not follow that of the standard, gradual change shown in Fig. 7(e). Reordering the learned receptive fields (their column location) gives Fig. 9(a). To reflect the new ordering, the reward table’s rows also need to be rearranged, which gives the reordered reward table Fig. 9(b), which shows the diagonal pattern typical of an ideal case (Fig. 10 shows a case where receptive fields were fixed Gabor patterns). Certain orientations are over expressed, such as the horizontal one, which could be fixed by including biologically motivated constructs such as lateral inhibition.

V. DISCUSSION

The main contribution of this work is that it put receptive field learning in the context of grounding. Thus, it provides a basis for a fully autonomous development of sensorimotor agents, where minimal initial states need to be specified (cf. the idea of Autonomous Mental Development [22]–[24]).

Also, the framework we presented here helps us view semantics in terms of pragmatics. As pointed out by Freeman, “meaning forms through action” [25] (p. 14). It is not what

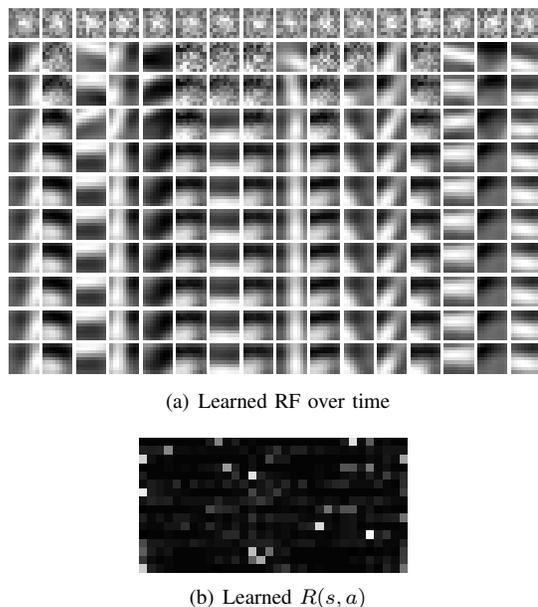


Fig. 8. **Learned Receptive Fields and $R(s, a)$.** (a) The learned RFs over time and (b) the final $R(s, a)$ are shown.

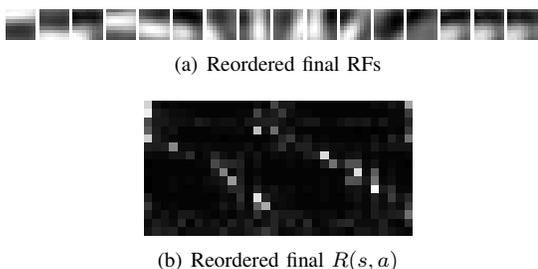


Fig. 9. **Reordered Learned Receptive Fields and $R(s, a)$.** (a) The receptive fields in Fig. 8 (the columns) were reordered to have a similar ordering as Fig. 7(e). (b) The rows in Fig. 8(b) were reordered accordingly, resulting in a reordered $R(s, a)$. Once reordered, the diagonal structure typical of an ideal reward table becomes apparent.

representations refer to, but how they are used that determine the meaning of those representations. Similar points have been raised by Bergson almost a century ago [26], and the importance of action as being central to nervous system function has been emphasized recently by others as well [27]–[30]. The emphasis of action nicely links to the increased use of reinforcement learning in vision-related tasks [31], [32] (also see works on Adaptive Dynamic Programming [33]).

A generally interesting question regards the intrinsic emergence of goals in autonomous agents [32], [34]. In this paper, we basically argued that the internal-state-invariance criterion is an (intrinsic) objective that serves the goal of understanding the external world properties (cf. “knowledge instinct” [35]). It would be interesting to investigate the evolutionary origin of such a “knowledge instinct”.

VI. CONCLUSION

In this paper, we showed that co-development of (1) receptive field properties and (2) action-based decoding/grounding

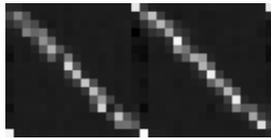


Fig. 10. **Learned $R(s, a)$ without RF Learning.** The reward table for an experiment (not reported in this paper) where the receptive fields were fixed Gabor patterns are shown, for comparison (cf. [16]).

schemes of those encodings is possible. Our framework suggests how, throughout the developmental period, encoding and decoding (grounding) processes in the brain can simultaneously mature while continuously influencing each other. We expect the conceptual framework presented here to facilitate deeper understanding about biological vision and about the precise role played by action.

ACKNOWLEDGMENT

The ideas in this paper and preliminary results were first presented in [36] as a poster.

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