

# How can bottom-up information shape learning of top-down attention-control skills?

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**Abstract**—How does bottom-up information affect the development of top-down attentional control skills during the learning of visuomotor tasks? Why is the eye fovea so small? Strong evidence supports the idea that in humans foveation is mainly guided by task-specific skills, but how these are learned is still an important open problem. We designed and implemented a simulated neural eye-arm coordination model to study the development of attention control in a search-and-reach task involving simple coloured stimuli. The model is endowed with a hard-wired bottom-up attention saliency map and a top-down attention component which acquires task-specific knowledge on potential gaze targets and their spatial relations. This architecture achieves high performance very fast. To explain this result, we argue that: (a) the interaction between bottom-up and top-down mechanisms supports the development of task-specific attention control skills by allowing an efficient exploration of potentially useful gaze targets; (b) bottom-up mechanisms boast the exploitation of the initial limited task-specific knowledge by actively selecting areas where it can be suitably applied; (c) bottom-up processes shape objects representation, their value, and their roles (these can change during learning, e.g. distractors can become useful attentional cues); (d) increasing the size of the fovea alleviates perceptual aliasing, but at the same time increases input processing costs and the number of trials required to learn. Overall, the results indicate that bottom-up attention mechanisms can play a relevant role in attention control, especially during the acquisition of new task-specific skills, but also during task performance.

## I. INTRODUCTION

Humans actively search task-relevant stimuli rather than passively processing all sensory information [9], [30]. Accumulating evidence indicates that top-down information rather than bottom-up, non task-specific mechanisms, dominates real-world image search processes, [6], [7], [15], [21]. Many recent studies focus on how various sources of top-down information are integrated [15]. Recent studies [20], [26] have explored how the active character of vision and the use of task-specific attention-control skills could affect the statistics of visual input and the structure of receptive fields. However, less attention has been devoted to the issue of how these skills are acquired, and the role played by the bottom-up information, available since the first exposition to a new task, during the acquisition process.

Numerous experiments, for example those using the *contextual cueing* paradigm, have shown that humans can develop visual exploration behaviours. These include bottom-up, stimuli-driven strategies and more sophisticated strategies in which cues are selected and used as landmarks [2]. In addition, human visual and motor strategies develop in a highly coordinated way, as it is especially evident during the learning of visuomotor tasks such as driving [13] or controlling a joystick [22], in which it is required that both visual and motor processes become coupled to the environment dynamics.

Given the human ability to develop attention-control skill for new tasks, one can ask *how* they are developed. The problem of how to efficiently and autonomously acquire an adequate top-down attention-control skill is also relevant from computational and applicative viewpoints because of its intrinsic difficulties.

A relevant aspect of the acquisition of novel skills is the concomitant development of a representation of the task to solve and of the attentional strategies to gather information relative to the same task. In other words, if the agent is not provided with a task representation (e.g., a target template encoded by hand by the programmer), it has to learn, at the same time, both to perform actions and to recognize what is relevant for performing such actions. This is apparently a chicken-and-egg problem, since before knowing what the task is it is difficult to fully recognize what information could be relevant, but at the same time without the ability to extract useful information, a task can hardly be learned.

The problem of how acquiring task-specific attention-control skills strategies is further complicated by the high dimensionality of visual input, the partial observability of the visual world, and the indirectness of their effects on action execution. Finally, since task-specific attention-control skills are often used to acquire the value of task-relevant variables, they can be reused for performing the same skill in novel situations without re-learning, provided that they embed abstract task regularities<sup>1</sup>

In this paper we explore the hypothesis that a bottom-up attention control mechanisms and the limited small size of

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<sup>1</sup>Structure learning [27] and other transfer learning techniques [24] address similar problems, but in most cases they cannot adapt to novel tasks without some learning.

the fovea play a relevant role during the learning of a novel visuomotor task, and can substantially contribute to solve the aforementioned problems.

To test this hypothesis we have implemented a neural architecture, which includes an arm controller and a gaze controller, and tested it in a “search-and-reach” scenario (Figure 2). In the experiment, the agent has to learn to find and touch, as quickly as possible, a red target in scenes which include also green salient elements having a fixed spatial relationship with the target (cues) and blue elements which appear in random positions (distractors). The system is based on a reinforcement learning method [25], and is rewarded only after successfully “touching” the target, not just for finding it with the eye.

To study how the learning process can be affected by both the active vision capabilities of the agent and the low level features of the visual scene, we analyzed the developmental trajectory of the system, and the impact of the acquired knowledge on performance during learning. The results indicate that the agent initially learns to move the eye away from highly salient cues, then learns the value of targets, and finally modifies the reaction to cues so as to consider them as landmarks that guide exploration.

## II. THE MODEL

This section overviews the architecture and explains the functioning of its components. The architecture (Figure 1) integrates two components: a bottom-up and top-down attention component, and an arm control component. These components are all based on three common bio-inspired computational principles: (a) population codes (here 2D neural maps) to represent sensorimotor information [18], [19]; (b) dynamic neural-field networks to integrate information and select actions through biased competition mechanisms [3], [8]; (c) a progressive development of skills (cf. [17]).

The setup used to test the model is a simulated version of a real system presented in [16]. The setup is composed of a down-looking camera set above a robotic arm. The arm working plane is a screen where the stimuli appear. The input image is used by a *periphery map* that implements bottom-up attention based on stimuli luminosity. The central part of the input image (*fovea*) is the input of a *reinforcement-learning actor-critic* component that learns to predict the spatial position of the rewarded arm targets with respect to the foveated cues, on the basis of the colour of the latter (top-down attention). A *potential action map (PAM)* accumulates activation, encoding the information on potentially interesting places to look next, on the basis of the seen stimuli. A *saliency map* integrates information from the periphery map and the PAM by summing their activation. The activation of the saliency map is then used to select the next eye movement on the basis of a neural competition. In particular, each fixation point, encoded in a *eye posture map*, suggests a potential arm target to an *arm posture map* where a neural competition takes place: when the eye fixates a location for enough time (3 time steps on average) a neuron cluster of the arm posture map reaches a threshold and triggers the action encoded by it. If the object reached with this action is the arm target, the

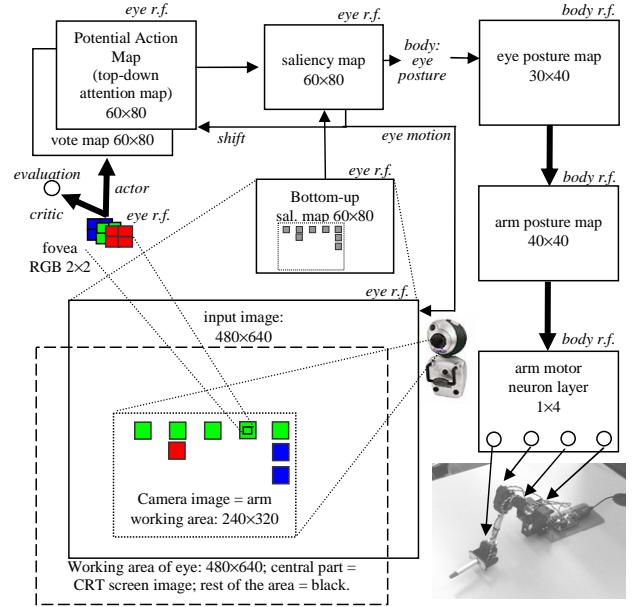


Fig. 1. Eye-arm control architecture.

system gets rewarded, otherwise it gets slightly punished (as a metaphor of energy consumption).

### A. Attention Control Components

*a) Periphery Map (Bottom-Up Attention):* The input image is a  $240 \times 320$  pixel RGB image. From this a  $30 \times 40$  gray periphery map  $\mathbf{pm}$  is extracted: first the input image is divided into  $30 \times 40$  blocks of  $8 \times 8$  pixels each, then the RGB color values of the pixels of each block are averaged to obtain a gray value. As objects (uniformly coloured squares) are shown on a black background, the simple gray image is enough to reveal their presence: a more sophisticated bottom-up saliency (e.g. as that of [11]) is not needed for the work purposes.

*b) Actor-Critic Component (Top-Down Attention):* The fovea is composed by a  $2 \times 2$  RGB pixel image (encoded in vector  $\mathbf{f}$ ) extracted from the centre of the input image. The fovea image is fed into two feedforward neural networks forming a reinforcement-learning actor-critic architecture [25]. The *critic* is a network with a linear output unit  $v_t$  which learns to evaluate the current state on the basis of the expected future discounted rewards. The system gets a reward  $r_t$  after the execution of a reaching action, and this, together with  $v_t$ , is used to compute the *surprise signal*  $s_t$  [25] used to update both the critic weights (vector  $\mathbf{w}^c$ ) and the actor weights (matrix  $\mathbf{W}^a$ ). The *actor* is a network whose output layer is a *vote map* of  $60 \times 80$  sigmoid neurons (with activation ranging within  $(-1, +1)$  and denoted with vector  $\mathbf{vm}$ ) which signal to the PAM the possible positions of rewarded targets with respect to the currently foveated visual cue ( $\gamma = 0.9$ ;  $T$  is the transpose operator):

$$v_t = \mathbf{w}^{cT} \mathbf{f} \quad s_t = (r_t + \gamma v_t) - v_{t-1} \quad (1)$$

$$\mathbf{vm} = g[\mathbf{W}^a \mathbf{f}] \quad g[x] = 1/(1 + e^{-x}) \quad (2)$$

The critic is trained on the basis of  $s_t$ , used as error signal, and the input  $\mathbf{f}$  [25]. The actor is trained with a Hebb rule involving

the activation of the saliency map (vector  $\mathbf{sm}_t$ ) encoding the last eye displacement (see below), and the input  $\mathbf{f}$ , with the purpose of increasing or decreasing the probability of doing the same saccadic movement again on the basis of the surprise signal  $s_t$  [16] ( $\eta^c = 10^{-7}$ ,  $\eta^a = 10^{-5}$ ,  $\bullet$  is the entrywise product operator):

$$\mathbf{w}_{t+1}^c = \mathbf{w}_t^c + \eta^c s_t \mathbf{f}_t \quad (3)$$

$$\mathbf{W}_{t+1}^a = \mathbf{W}_t^a + \eta^a s_t \mathbf{sm}_t \bullet (\mathbf{vm}_t \bullet (1 - \mathbf{vm}_t)) \mathbf{f}_t^T \quad (4)$$

*c) Potential Action Map (Top-Down Attention Memory):* The PAM is formed by  $60 \times 80$  leaky neurons (vector  $\mathbf{pam}$ ) and accumulates evidence, furnished by the vote map  $\mathbf{vm}$  via topological connections, on the possible positions of rewarded targets. Importantly, during each saccade the map activation is shifted in the direction opposite to the eye motion to maintain eye-centred representations (as it might happen in real organisms, see [5]). The PAM is reset each time the input image changes (also this might happen in real organisms [12]).

*d) Saliency Map:* The  $60 \times 80$  saliency map (encoded in vector  $\mathbf{sm}$ ) selects saccade movements on the basis of the sum of the topological input signals  $\mathbf{pm}$  and  $\mathbf{pam}$ . The saccade movement is selected by first identifying the unit with the maximum activation and then by activating the map with a Gaussian population code centred on it (the Gaussian function has a width  $\sigma = 1$ ). The eye movement is the average of the winning neurons' preferred eye displacement ( $\Delta x, \Delta y$ ). This selection mechanism, based on the maximum function, is a computationally fast approximation of a biased dynamic competition process (e.g., cf. [8]).

*e) Biology:* Empirical evidence indicates that the cortical area of the frontal eye field (FEF) exhibits properties similar to those of the saliency map integrating bottom-up and top-down information to drive overt and covert attention [28]. Another possible location for this integration is the posterior parietal cortex [29]. Bottom-up (pre-attentive) saliency processes take place in parallel in relation to various aspects of the retina image such as color, orientation, and motion, and the resulting information is integrated at higher levels such as the FEF and the parietal cortex. These processes are performed with increasing abstraction in the retina, the lateral geniculate nucleus, the visual cortex, and the extrastriate visual cortex. The top-down influence on attention control mainly originates from prefrontal cortex based on the subject's goals and motivations and the environment context. One type of top-down influence reaching FEF neurons is related to the spatial relationship between objects, which humans can acquire unconsciously, as shown in experiments on contextual cueing [2]. This kind of knowledge might be encoded in the hippocampal system. Neurobiological data on how and where saliency maps can be implemented in the brain can be found in [4], [23], [29]. The trial-and-error learning processes performed by the model might correspond to the processes taking place in the portions of the basal ganglia dedicated to eyes control (striatum and substantia nigra pars reticulata [10]).

### B. Arm Control Components

This section presents the main aspects of the arm control components. Only the broad features of these components are

presented here as they are less relevant for the focus of this research (see [17] for more details).

*f) Eye Posture Map:* This  $30 \times 40$  neuron map encodes the current eye posture as a Gaussian population code  $\mathbf{emp}$  ( $\sigma = 0.3$ ).

*g) Arm Posture Map:* This  $40 \times 40$  map (vector  $\mathbf{apm}$ ) represents the output layer of a neural network pre-trained with a Kohonen algorithm and encodes arm postures in the 2D map space. A neural biased competition [8] takes place in the map (similarly to what happens in real organisms [3]) in order to select a target for reaching actions when any neuron achieves a certain threshold.

*h) Arm Posture Readout Layer:* This layer includes four sigmoid neurons (vector  $\mathbf{apr1}$ ) that encode the desired arm joint angles issued to the arm simulated servos. The map is activated by the arm posture map through connection weights encoded in the matrix  $\mathbf{W}^{apr1}$ .

*i) Training:* The arm components were trained before the experiments illustrated in Section 1. Pre-training is divided in three learning phases using *motor babbling* (i.e., random movements of the arm), in which the system: (a) performs a vector quantization of postures within the arm posture map on the basis of a Kohonen algorithm; (b) learns the inverse kinematic mapping ( $\mathbf{W}^{apm}$ ) between the gaze directions corresponding to the seen hand ( $\mathbf{epm}$ ) and the corresponding arm posture ( $\mathbf{apm}$ ) with a delta rule; (c) trains the arm posture readout map ( $\mathbf{W}^{apr1}$ ) with a delta rule.

## III. EXPERIMENTAL SETUP

The environment (Figure 2) is a  $6 \times 5$  grid with "objects" (coloured squares) on some of its vertexes. The objects are: 2 to 5 green cues having 100% luminosity and forming a (randomly placed) vertical line; 1 red target having 80% luminosity and placed on the left of the cue line; 2 to 5 blue distractors having 80% luminosity and randomly placed in the remaining grid vertexes (so they are not spatially related to the target).

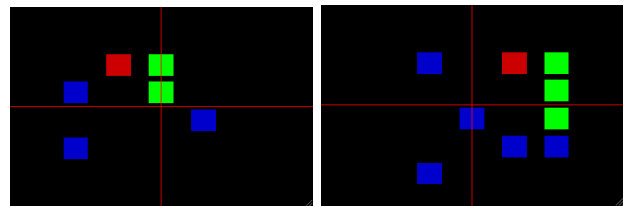


Fig. 2. Examples of environments used in the experiment.

## IV. RESULTS

### A. Analysis of performance and behaviour

Figure 3 shows the average reward received by the robot for every reaching action during learning. After only 20 trials the performance increases rapidly to 0.5, and at 60 it reaches a near-optimal steady state. Figure 4 shows how the average number of saccades per reaching action evolves during learning. Initially 16 saccades are executed per trial. After 15 trials their number rises to a maximum of 26 (in correspondence to the maximum learning progress in reaching),

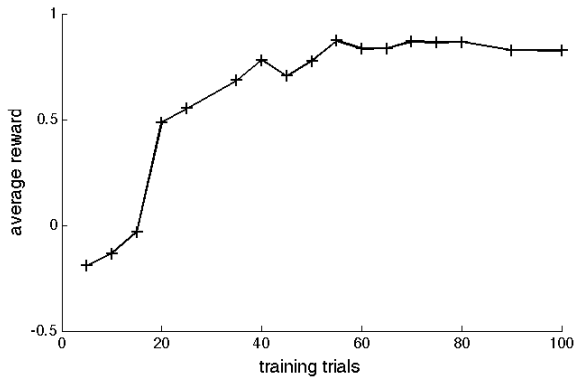


Fig. 3. Evolution of average reward per training trials. For each marked number of trials, data were collected by running the system for 1000 trials (during which learning was stopped) and then by averaging the resulting performance.

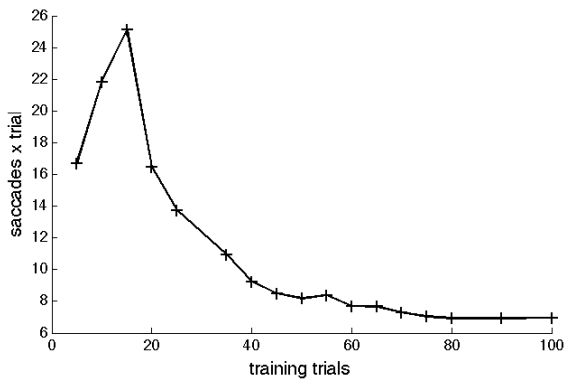


Fig. 4. Evolution of average saccade number per training trials. For each marked number of trials, data were collected by running the system for 1000 trials (during which learning was stopped) and then by averaging the resulting saccade per trial.

and then progressively decreases. Considering that the agent takes three or four time steps to trigger a reaching action, the results indicate that the agent is able to find the target in about three saccades. The agent achieves this performance by acquiring and using knowledge about spatial relationships between objects. In particular it usually first foveates a cue (thanks to its high luminosity), and then an object on the left of the cue line. If this object is the target, the system foveates it few times until the arm reaching action directed to it is triggered, whereas if it is a distractor the system directly foveates another object at the left of the cue line and this is usually the target (see [16] for more details).

### B. Analysis of the learning dynamics

Figure 5 shows the evolution of the expected value for each foveated object produced by the critic during learning. The graph shows that the cue expected value becomes negative after few trials. After about 5 trials, also the target and distractor assume a negative value. When the importance of the target is discovered (trial 15), its value increases rapidly. Successively, the value of the cue starts to increase again. Finally, also the value of the distractor increases. This indicates that the learning dynamics are strongly affected by the saliency

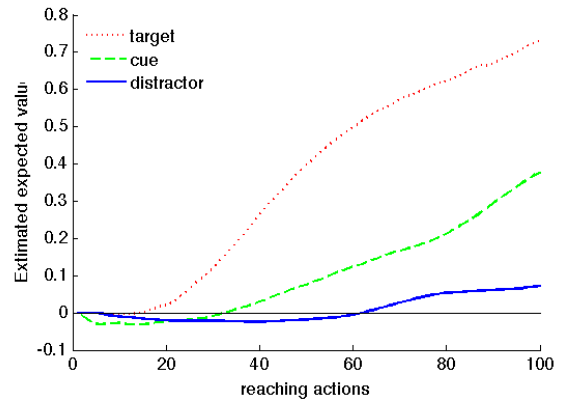


Fig. 5. Evolution of the critic estimated evaluation during learning for the target, cues, and the distractors.

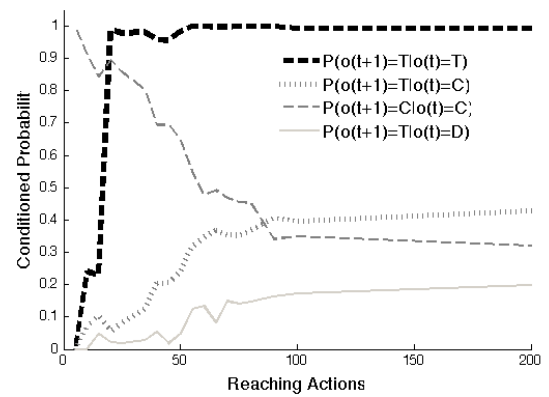


Fig. 6. Evolution of conditional probability of foveating a kind of object given the previous foveated object.  $T$  = target,  $C$  = cue,  $D$  = distractor,  $t$  is the time index. As an example,  $P(o(t+1) = T|o(t+1) = C)$  is the probability of observing  $T$  at time  $t+1$  given the observation of  $C$  at time  $t$ .

of the objects that are present in the environment, in particular that the cues (having a higher visual saliency due to their high luminosity) are learned before the distractors (lower luminosity). It also shows that the target has a very high expected value as its foveation preludes to its arm reaching and hence the reward attainment and that cues have a value higher than distractors due to their spatial relations with the target.

Figure 6 illustrates the evolution of the conditional probability of foveating a kind of object given a certain type of previously foveated object. The graph shows that the system first develops the skill of avoiding to stay on cues (gray dashed line, first 10 trials). Then, it quickly develops the skill of staying on the target (bold dashed line, first 20 trials). Then, it acquires the skill of moving from the cues to the target (dotted line, first 100 trials). And finally, it learns to move from the distractors to the target (gray line, until 200 trials). This developmental pattern explains the peak of saccades (after 20 trials) shown in figure 4. This peak separates two phases: first, the system learns to inhibit the most salient objects (cues) so as to be capable of exploring the rest of the scene (in this perspective, it learns to treat the cues as “distractors” to be avoided), and later it learns to exploit such cues as

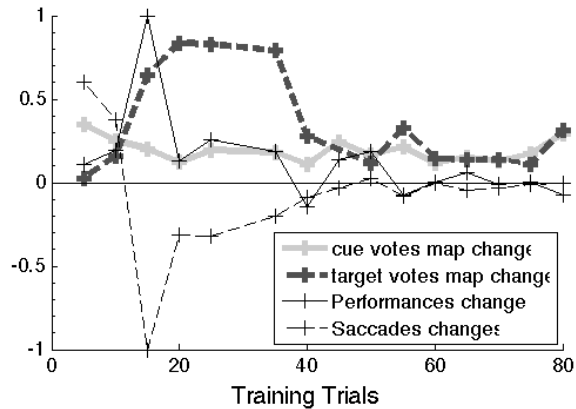


Fig. 8. Comparison of changes of: (a) performance; (b) saccade number; (c) vote map activations when the system foveates the target; (d) vote map activations when the system foveates the cue. The vote map activation is the average activation of the map units, taken with absolute value. The changes were computed as the difference between the values of two succeeding steps. The data were normalised in (-1, +1) by computing the maximum values reached in 1000 trials (the graphs reports only the initial learning phase).

landmarks to find the target. These dynamics indicate that the learning process has distinct phases whose order is affected by the saliency of objects, the relevance of their information content for accomplishing the task, and the knowledge and skills acquired by the system until a certain moment.

### C. Evolution of internal representations

Figure 7 shows the evolution of the vote map during learning and how object representations are learned. This evolution confirms the analysis of the developmental phases illustrated above. The agent initially learns to inhibit the cues (see Figure 7a); in this time interval, the target map does not change in a relevant way (Figure 7f). Successively (after trial 20), the vote map activation for the target quickly achieves its steady level (Figure 7h-j). At this point the vote map activation for the cues slowly develops its capacity to guide the eye towards positions at the left of the cue line where the system might find the target. After enough trials the cues become the main landmarks to guide the eye to the target. Figure 8 shows the average change of the vote map activation (caused by the perception of the cue or the distractor) during learning and compares it with the improvements of performance and number of saccades. The change of the votes for the target take place mainly between trial 20 and trial 40. The knowledge of the agent from trial 15 to 20 changes only in terms of the acquisition of a small bias to move away from the cues (Figure 7b), the related tendency to non-revisit such cues (as the PAM maintains a memory of them), and a small bias to stay on the target (Figure 7g). The bottom-up saliency leads to boost the value of this knowledge as it guides the system to explore regions of the environment where there are potentially relevant objects (vs. “empty” less interesting regions) and to systematically apply such knowledge to them. As a consequence, although minor this change of knowledge causes a relevant change in performance. Indeed, although the system has still little knowledge on the spatial relationship between the cues and the target, it manages to achieve the

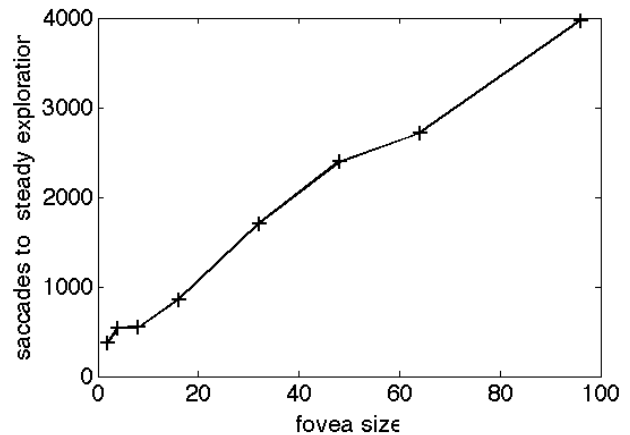


Fig. 9. Change of the learning performance with an increasing fovea size. Y-axis reports the total number of saccades necessary for an agent to acquire a stable exploration behaviour ( average length of 7 saccades). X-axis reports the size in pixels of one side of the square fovea (2,4,8,16,32,48,64,96). Note that a fovea sized 96x96 pixels can allow perceiving 3x3 close objects at the same time. The data are the average of 5 runs executed for each different fovea size. All other results reported in the paper refer to a fovea size of 2x2 pixels.

target in about 50% of trials. This dynamics prelude to learning more sophisticated exploration strategies based on the spatial relations existing between the objects.

### D. Role of the fovea size in learning performance

Figure 9 shows how the number of saccades necessary to learn the task increases with the size of the fovea (the maximum size allows the system to see 3x3 close objects). A possible explanation is that a small fovea can get rid of the context more easily; this is achieved since a small fovea stores only local information, which is however sufficient to achieve good performance when information is selected actively and a wrong saccade execution has low cost. Adding information does not change performance significantly while at the same time slows learning.

## V. DISCUSSION

The simple experiment reported here shows how, during learning, bottom-up information favors the acquisition of top-down attentional control skills. In the first experiences of the task, bottom-up mechanisms prevent the system from exploring useless parts of the environment (e.g. where there are no objects), and drive the eye to most salient regions of space where potentially relevant objects might be found. As pointed out in [14], this leads the system to “produce a dynamic coupling with the environment that allows the structuring of input, and produces statistical regularities” that are progressively assimilated into the top-down components in different phases of development, so rendering exploration increasingly efficient.

The experiment shows in particular that, during learning, the bottom-up saliency of objects provides the basis for discovering and defining their role. Initially most salient objects, explored most frequently, tend to be encoded as obstacles

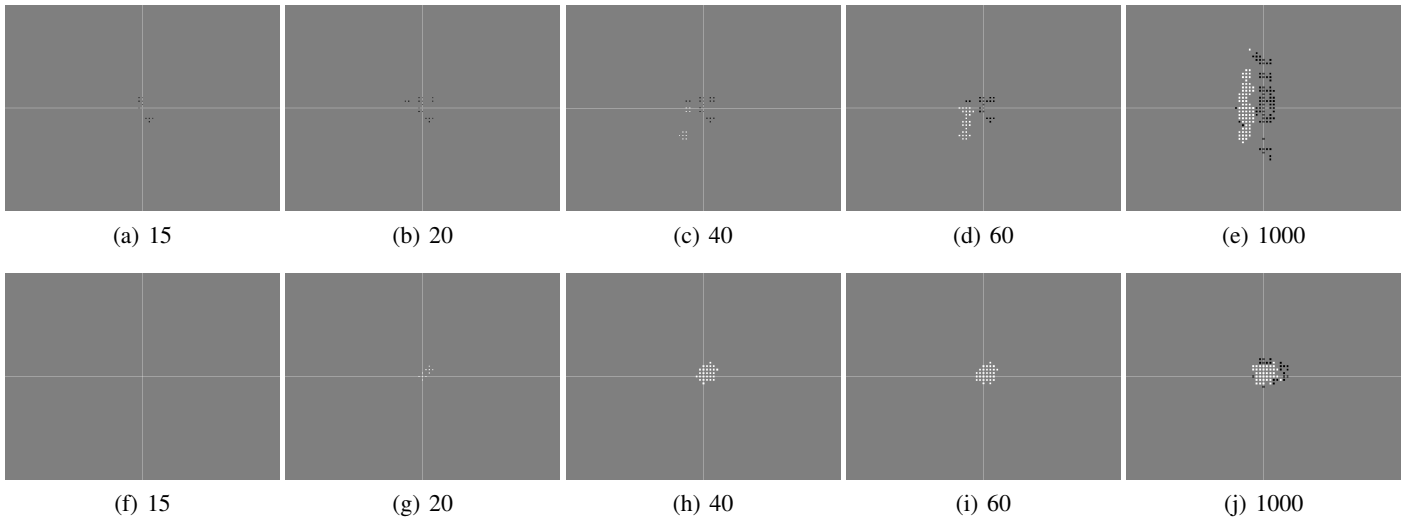


Fig. 7. Evolution of the vote map activation during learning when the system foveates a cue (a-e) or the target (f-j). White and black dots indicate the activation of neurons activated respectively above or below zero (the size of the dots indicates the distance of the activation from this value). Numbers indicate the trial during learning.

or distractors to be avoided if the system is not capable of exploiting their spatial relations with the target (or, in general, if these relations do not exist). Successively, the system discovers the objects which are most relevant for the task (targets) and learns to focus attention on them and to obtain reward by reaching them. Finally, objects that were previously avoided can change their role and become landmarks used for finding the target if they have useful spatial relationships with the target.

Once the system has acquired the top-down attention skills, these skills continue to rely on the bottom-up mechanisms to correctly function. For example, the different luminosity of objects is exploited to organise exploration. Moreover, the acquired top-down skills are systematically applied to several different objects explored on the basis of their bottom-up saliency. In this respect, even when top-down attention-control skills are partially formed, bottom-up mechanisms can boost their utility by providing guidance on where to apply them.

The limited dimension of the fovea help this process, too, because it reduces the input size of the adaptive mechanism, which then requires less learning examples to acquire the initial skills. Indeed, although a bigger fovea alleviates the perceptual aliasing problem, its higher demands in terms of computational requirements and learning time make it unfavorable. Taken together, the results show that bottom-up mechanisms and the fovea structure can have a great influence on the development of top-down attention-control skills in adaptive active vision systems.

One of the main critique that can be raised to this work is that it relies entirely on the assumption that a totally task independent bottom-up mechanism exists. Although most studies, reviewed in the introduction, support the idea of a predominance of top-down and task-specific control of attention, it should be noted that without prior knowledge of the task an agent needs a “baseline” exploration policy such as the one described here (or, alternatively, a predefined set of priors relative to the structure of the problem [27]). In this respect,

however, this study indicates that not only the baseline policy governs attentional control when top-down control is missing, but it also supports its acquisition by focusing exploration on salient visual stimuli whose role is initially unknown, and can even support top-down attentional skills once they have formed.

The current limitations of the architecture are that it uses a simplified bottom-up mechanism, addresses only one kind of top-down knowledge (i.e., knowledge of spatial relations among objects, see [15]), and is based on an inflexible coupling between attention and arm-action control (but consider that this strong assumption is quite in line with the *attention for action* principle [1], [16]). In addition, the experimental setup used to test the model was based on rather simplified and static input images. These elements pose some limits on the generality of the presented results, but at the same time they permitted to study the problem of task-specific attention-control learning without having to tackle the difficulties involved with the use of a general purpose visual system and this greatly helped to analyse the results. We plan to overcome these limitations in future work, and to be able to perform a systematic comparison of the model behaviour with the one reported in studies on human attention learning.

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