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# Bayesian models of eye movement selection with retinotopic maps

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**Abstract** Among the various possible criteria guiding eye movement selection, we investigate the role of position uncertainty in the peripheral visual field. In particular, we suggest that, in everyday life situations of object tracking, eye movement selection probably includes a principle of reduction of uncertainty. To do so, we confront the movement predictions of computational models with human results from a psychophysical task. This task is a freely moving eye version of the Multiple Object Tracking task with the eye movements possibly compensating for lower peripheral resolution. We design several Bayesian models of increasing complexity, whose layered structures are inspired by the neurobiology of the brain areas implied in eye movement selection. Finally, we compare the relative performances of these models with regard to the prediction of the recorded human movements,

and show the advantage of taking explicitly into account uncertainty for the prediction of eye movements.

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## 1 Introduction

We usually make a few saccades per seconds. Saccades, and other eye movements, may result from a decision on where to look next, in order to gain information about the visual scene by driving the fovea towards regions of interest. However, the sensitivity and spatial resolution decays towards the periphery of the visual field. As a result, we are uncertain about what we expected to learn from an eye movement towards a more peripheral position. The uncertainty is a common issue for both perception – because we can not be sure of what we perceive – and action – because we can not be sure of the consequences of our action. In this paper, we investigate the possible role of uncertainty evaluation in selection processes related to active perception. We build a Bayesian model inspired by the neurophysiology of eye movement selection related brain regions, in order to investigate eye movements selection during freely moving eye Multiple Object Tracking task (MOT).

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Bayesian methodology

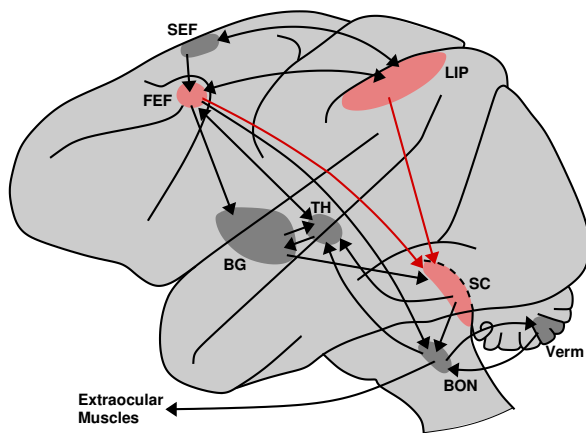
In order to handle and reason taking into account uncertainty, we use the Bayesian Programming framework (Lebeltel et al 2004; Bessière et al 2008). This framework provides a systematic procedure to build and use a Bayesian model. A Bayesian model uses probability distributions to represent knowledge with uncertainty. It then reasons about this knowledge by applying the probabilistic rules. More precisely, starting from a joint probability distribution, marginalization, and Bayes' rules allow to compute any conditional or marginal probability distribution. As this joint probability is usually of very high dimensionality, we use conditional independence hy-

potheses to decompose the joint distribution in a simpler product of smaller distributions.

In the end, a Bayesian programmer specifies a set of variables, a *decomposition* of the joint probability distribution and a mathematical expression for each factor that appears in this decomposition. At that point, any distribution on the variables can be computed. The programmer is usually interested on one particular distribution, which is called a *question*. The inference can be automatically computed through the use of both marginalization and Bayes rules.

### Eye movement circuitry

Even if we do not have the pretension to build a complete model of the neurophysiology of the eye movement selection related brain regions, the structure of our model is inspired by their anatomy and electrophysiology. Saccadic and smooth pursuit circuitry share a large

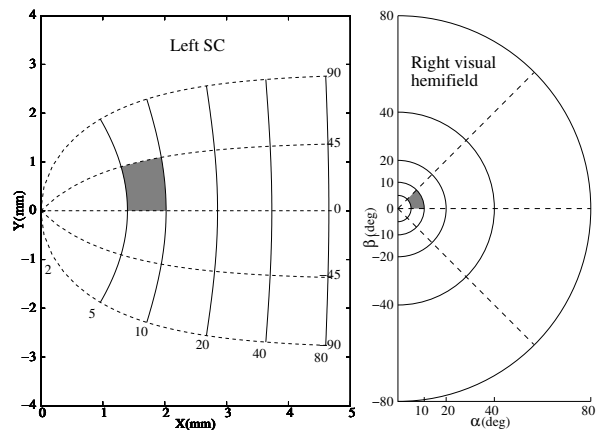


**Fig. 1** Premotor and motor circuitry shared by saccade and smooth pursuit movement (Macaque monkey). BG: basal ganglia, BON: brainstem oculomotor nuclei, FEF: frontal eye fields, LIP: lateral bank of the intraparietal sulcus, SC: superior colliculus, SEF: supplementary eye fields, TH: thalamus, Verm: cerebellar vermis. In red: regions using retinotopic reference frames to encode visual, memory and motor activity, refer to text for more details. Adapted from (Krauzlis 2004).

part of their functional architecture (Krauzlis 2004). Among those regions containing saccadic and smooth pursuit subcircuits (Fig. 1), the superior colliculus (SC), the frontal eye fields (FEF) and the lateral bank in the intraparietal sulcus (LIP) in the posterior parietal cortex have a number of common points. They all receive information concerning the position of points of interest in the visual field (visual activity), memorize these positions (delay activity) and are implied in the selection of the gaze targets among these points (presaccadic activity) (Moschovakis et al 1996; Wurtz et al 2001; Scudder et al 2002). These positions are encoded by cells with receptive/motor fields defined in a retinotopic reference

frame. Our model is based on retinotopic probability distributions encoding similar informations (observations, memory of target positions, motor decision).

In the SC, these cells are clearly organized in topographic maps, in various species (Robinson 1972; McIlwain 1976, 1983; Siminoff et al 1966; Herrero et al 1998). In primates, these maps have a complex logarithmic mapping (Fig. 2) (Robinson 1972; Ottes et al 1986), similar to the mapping found in the striate cortex (Schwarz 1980). Concerning the FEF, mapping studies clearly show a logarithmic encoding of the eccentricity of the position vector (Sommer and Wurtz 2000), however complementary studies are necessary to understand how its orientation is encoded. Finally, the structure of the LIP maps is still to be deciphered, even if a continuous topographical organization seems to exist, with an over representation of the central visual field (Ben Hamed et al 2001). Given the lack of quantitatively defined FEF and LIP mappings, we assume that they share similar properties with the SC one and thus use the log complex mapping of the SC for all the position encoding variables of our model.



**Fig. 2** Macaque collicular mapping. The angular position of targets in the visual field (right) are mapped onto the SC surface (left) using a logarithmic mapping. The grey areas represent the same part of the visual field in both representations.

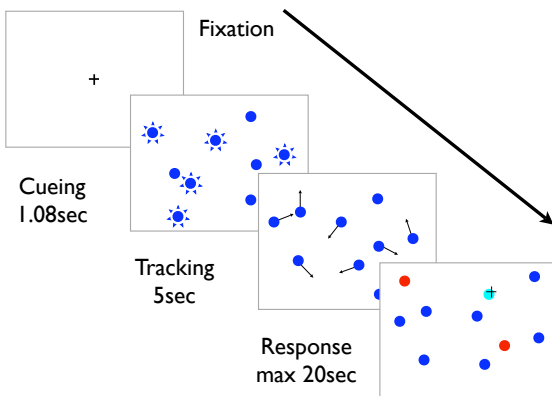
The neurons related to the spatial working memory in SC (Mays and Sparks 1980), FEF (Goldberg and Bruce 1990) and LIP (Gnadt and Andersen 1988; Barash et al 1991a,b) – also called quasi-visual cells or QV – are capable of dynamic remapping. These cells can be activated by a memory of the position of a target, even if the target was not in the cell’s receptive field at the time of presentation. They behave as if they were included in a retinotopic memory map, integrating a remapping mechanism allowing the displacement of the memorized activity when an eye movement is performed. Neural network models of that type of maps, either in the SC or the FEF, have already been proposed (Droulez and Berthoz 1991;

Bozis and Moschovakis 1998; Mitchell and Zipser 2003). Such a mechanism, adapted to Bayesian programming, is used in the representation and memory layers of our model.

To summarize, though not strictly neuromimetic, the layered structure of our Bayesian model is based on log complex retinotopic maps with remapping capabilities, encoding the filtered visual input, the memorized position of targets of interests, and the generation of motor commands.

### Experimental protocol

In order to study selection of eye movement in a controlled task, we use eye movement recordings from a freely moving eye version (Tanner et al 2007) of the classical MOT task (Pylyshyn and Storm 1988). Eye movements in MOT have only recently attracted interest (Tanner et al 2007; Fehd and Seiffert 2008; Zelinsky and Neider 2008). The original task was designed to investigate the distribution of covert attention with eye movements constrained by a fixation cross (Cavanagh and Alvarez 2005), while we looked at how free eye movements might optimize the tracking. Figure 3 illustrates this experiment in which participants are presented with a set of targets among a number of distractors. All of these objects are indiscernible  $1^\circ$  large discs and move in a quasi-random pattern. The task is to remember which of these objects are the targets (see appendix A for a complete description). With this experimental paradigm, the visual scene is composed of simple geometric features therefore allowing for a study of the eye movement selection that occurs in this context.



**Fig. 3** Typical Multiple Object Tracking experiment. A set of simple objects is presented, the targets are identified as the flashing ones, then the flashing stops and all the objects move around independently. After they stop moving, the subject must identify the targets.

First we describe the Bayesian models we propose. Then we present the global results indicating that uncertainty is useful and some specific situations shedding light on the differences between the models.

## 2 Methods

The model we propose is composed of two parts. The first part deals with the perception and memory of the visual scene (*representation* model). The second part deals with the actual selection of where to look next (*decision* model).

Both models are expressed in a retinal reference frame, with a logcomplex mapping as explained above.

### 2.1 Representation

The representation part of our model is a dynamic retinotopic map of the visual environment. This representation is structured in two different layers. The first layer is concerned only with the integration of the visual input, i.e. the occupancy of the visual scene without any discrimination between targets and distractors (*occupancy grid*), it is the model homologous to the visual cells.

The second layer is a memory of the position of the targets, reminiscent of the QV cells. It represents the knowledge of the observer about the position of the targets, based on the occupancy representation.

*Occupancy grid* Occupancy grids are a standard way to represent the state of an environment. They were originally introduced for the representation of obstacles in robotics applications (Elfes 1989). The general idea is to discretize the environment into a grid and to assign a variable in each cell of the grid stating whether there is an obstacle or not. The occupancy grid is therefore the collection of probability distributions over each variable in the grid.

We apply this model to the presence of objects in the visual field. More precisely, we introduce a collection  $O$  of binary variables  $O_{(x,y)}^t$ , one for each timestep  $t \in \llbracket 0, t_{max} \rrbracket$  and location  $(x, y) \in \mathcal{G}$  where  $\mathcal{G}$  is a regular grid in the retino-centered logcomplex reference frame.<sup>1</sup> We also assume that we have visual inputs in this same reference frame, represented by a collection  $V$  of binary variables  $V_{(x,y)}^t$  for  $t \in \llbracket 1, t_{max} \rrbracket$  indicating if an object (either target or distractor) is perceived in the corresponding cell. Finally, we include some past eye movement information  $M^t$  in order to model the remapping

<sup>1</sup> Omission of an index or exponent in the variable name indicates the conjunction of all of those variables for the missing index varying in its full range:  $O = O^{0 \rightarrow t_{max}} = \bigwedge_{t=0}^{t_{max}} O^t = \bigwedge_{t=0}^{t_{max}} \bigwedge_{(x,y) \in \mathcal{G}} O_{(x,y)}^t$

capability exhibited by cortical and subcortical retino-centered memories.

We write the joint probability distribution over all these variables by assuming the occupancy of the cells are independent one from another conditionally to the past eye movement and the former state of the grid. We also assume that the observation corresponding to a cell is independent on all other variables conditionally to the current occupancy in this cell. This is summarized by the following factorization of the joint distribution:

$$\begin{aligned} P(O V M) &= P(O^0) \prod_{t=1}^{t_{max}} P(O^t V^t M^t | O^{t-1}) \\ &= \prod_{(x,y) \in \mathcal{G}} P(O_{(x,y)}^0) \\ &\quad \times \prod_{t=1}^{t_{max}} \left[ P(M^t) \times \prod_{(x,y) \in \mathcal{G}} \left[ P(O_{(x,y)}^t | M^t O^{t-1}) \right] \times P(V_{(x,y)}^t | O_{(x,y)}^t) \right] \end{aligned}$$

In this expression,  $P(O_{(x,y)}^0)$  is an arbitrary prior on the occupancy of the visual scene,  $P(M^t)$  is a distribution over the eye movement that can be chosen arbitrarily as the results of the inference do not depend on it, as far as it is non zero for the actual eye movements observed. The relation between the occupancy and the observation,  $P(V_{(x,y)}^t | O_{(x,y)}^t)$ , is a simple probability matrix chosen to state that there is a high probability of observing an object when there is one and conversely of not observing anything when there is nothing.

The evolution of the grid, with the remapping capability, is specified by the transition model,  $P(O_{(x,y)}^t | M^t O^{t-1})$ , which essentially transfers the probability associated to antecedent cells for the given eye movements to the corresponding present cell with an additional uncertainty factor (see appendix B.1 for details).

With this description, updating the knowledge over the occupancy of the visual field corresponds to the following question for each time  $t$ :

$$P(O^t | V^{1 \rightarrow t} M^{1 \rightarrow t}) \quad (1)$$

where  $V^{1 \rightarrow t}$  is the conjunction of all variables  $V^u$  for  $u \in \llbracket 1, t \rrbracket$ . This expression can be computed in an iterative manner using Bayesian inference:

$$\begin{aligned} P(O^t | V^{1 \rightarrow t} M^{1 \rightarrow t}) &\propto \prod_{(x,y) \in \mathcal{G}} P(V_{(x,y)}^t | O_{(x,y)}^t) \\ &\quad \times \sum_{O^{t-1}} \left[ \prod_{(x,y) \in \mathcal{G}} P(O_{(x,y)}^t | M^t O^{t-1}) \right] \times P(O^{t-1} | V^{1 \rightarrow t-1} M^{1 \rightarrow t-1}) \end{aligned}$$

However, this expression comprises a summation over all possible grid states, which is computationally intensive. Therefore we approximate the inference over the

whole grid by a set of inferences for each cell that depend only on a subset of the grid:

$$\begin{aligned} P(O_{(x,y)}^t | V^{1 \rightarrow t} M^{1 \rightarrow t}) &\propto P(V_{(x,y)}^t | O_{(x,y)}^t) \\ &\quad \times \sum_{O_{\mathcal{A}(x,y)}^{t-1}} \left[ P(O_{(x,y)}^t | M^t O_{\mathcal{A}(x,y)}^{t-1}) \times \prod_{\mathcal{A}(x,y)} P(O_{(x',y')}^{t-1} | V^{1 \rightarrow t-1} M^{1 \rightarrow t-1}) \right] \end{aligned}$$

where  $\mathcal{A}(x, y)$  is the subset of the cells  $(x', y')$  of the grid that are the antecedent of the cell  $(x, y)$  by the current eye movement  $M^t$ .

*Positions of the targets* The previous model allows for the description of the visual scene without differentiating between targets and distractors. In order to introduce this difference, we add a set of variables  $T_i^t$  to represent the location of each target  $i \in \llbracket 1, N \rrbracket$  at each time  $t \in \llbracket 0, t_{max} \rrbracket$  in the logcomplex retino-centered reference frame.

This representation is the standard way to represent the location of some objects and serves a different purpose than the occupancy grid, which is only the representation of the visual scene.

The model is extended with this additional variables by adding a new factor in the joint distribution,  $P(T_i^t | T_i^{t-1} O^t M^t)$ , that represents the dynamic model of targets:

$$\begin{aligned} P(O V M T) &= \prod_{(x,y) \in \mathcal{G}} P(O_{(x,y)}^0) \prod_{i=1}^N P(T_i^0) \\ &\quad \times \prod_{t=1}^{t_{max}} \left[ P(M^t) \times \prod_{(x,y) \in \mathcal{G}} \left[ P(O_{(x,y)}^t | M^t O^{t-1}) \right] \times P(V_{(x,y)}^t | O_{(x,y)}^t) \right] \times \prod_{i=1}^N P(T_i^t | M^t O^t T_i^{t-1}) \end{aligned}$$

The additional factors  $P(T_i^0)$  are priors over the positions of the targets that can be set according to the starting position of the targets as shown in the cueing phase.

The dynamic model of targets is very similar to the dynamic model of objects but with the occupancy grid on objects as observation (see appendix B.2 for details).

At each time step, the relevant state of the representation can be summarized by the following question for each target  $i \in \llbracket 1, N \rrbracket$  at each timestep  $t \in \llbracket 1, t_{max} \rrbracket$ :

$$P(T_i^t | V^{1 \rightarrow t} M^{1 \rightarrow t}) \quad (2)$$

Bayesian inference leads to the following expression for this question:

$$\begin{aligned} P(T_i^t | V^{1 \rightarrow t} M^{1 \rightarrow t}) &\propto \sum_{O^t} \left[ \sum_{O^{t-1}} \left[ P(T_i^t | M^t O^t T_i^{t-1}) \right] \times P(O^t | V^{1 \rightarrow t} M^{1 \rightarrow t}) \right] \times P(T_i^{t-1} | V^{1 \rightarrow t-1} M^{1 \rightarrow t-1}) \end{aligned}$$

where  $P(T_i^{t-1} | V^{1 \rightarrow t-1} M^{1 \rightarrow t-1})$  is the result of the same inference at the preceding timestep,  $P(O^t | V^{1 \rightarrow t} M^{1 \rightarrow t})$  the result of question 1 at the same timestep. The summation of the whole grid, which is still computationally intensive, can be approximated as above, by separating the cells.

Both questions 1 and 2 are the current knowledge about the visual scene that can be inferred from the past observations and movements and the hypotheses of our model.

## 2.2 Decision models

Based on this knowledge, we decide where to look next in order to solve the task. We propose different models in order to test different hypotheses. First, we make the hypothesis that this representation model is useful for producing eye movements. To test this hypothesis, we compare a model that does not use the representation with one that does.

Then, the main hypothesis is that uncertainty, explicitly taken into account, can help in the decision of eye movement. Therefore, we compare a model that does not take into account explicitly the uncertainty with one that does.

In the end, we need to specify three models: one that does not use the representation model ( $\pi_A$ ), one that uses the representation model without explicitly taking into account uncertainty ( $\pi_B$ ), and finally one that uses the representation model and explicitly takes into account uncertainty ( $\pi_C$ ). Each model  $\pi_k$  will infer a probability distribution on the next eye movement represented by a new variable  $C^t \in \mathcal{G}$  at each time  $t \in [1, t_{max}]$ :

$$P(C^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_k)$$

This variable is the model's homologous to the motor cells found in LIP, FEF and SC.

*Constant model* This constant model is a baseline for the other models. We need the best static probabilistic distribution that can account for the experimental eye movement. Formally it is specified as being independent on time and on the observations:

$$\begin{aligned} \forall t \in [1, t_{max}], P(C^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_A) \\ = P(C^t | \pi_A) = P(C^1 | \pi_A) \end{aligned}$$

In these conditions, it can be shown that the best distribution  $P(C^1 | \pi_A)$ , according to the measure defined section 3.1, assigns the probability of each individual discretized motion to be equal to its frequency in the experimental data.<sup>2</sup> Therefore, we learned this distribution from our experimental data, using only a randomly selected subset in order not to overfit our models.

<sup>2</sup> When restricted to time independence and assuming a uniform prior over such models, our measure is a multinomial likelihood which leads to a Dirichlet distribution according to the experimental frequencies. The maximum of this Dirichlet distribution is the histogram of the experimental frequencies.

*Targets positions* The second model we propose uses the knowledge from the representation layer to determine its eye movements. More precisely, it tends to look at locations where targets are near, in a kind of fusion process. Its prior will follow the statistical distribution of eye movements and the likelihood will be based on the distributions on the targets location inferred in the representation layer.

The decomposition is as follows:

$$\begin{aligned} P(C V M T | \pi_B) \\ = \prod_{t=1}^{t_{max}} \left[ \begin{array}{l} P(V^t M^t | \pi_B) \\ \times \prod_{i=1}^N P(T_i^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_B) \\ \times P(C^t | T^t \pi_B) \end{array} \right] \end{aligned}$$

where:

- $P(V^t M^t | \pi_B)$  is an arbitrary prior that is not used in the inference,
- $P(T_i^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_B)$  is the result of inference 2,
- $P(C^t | T^t \pi_B)$  is the result of the inference in a fusion submodel over the targets that yields:

$$P(C^t | T^t \pi_B) \propto P(C^t | \pi_A) \prod_{i=1}^N P(T_i^t | C^t)$$

where  $P(C^t | \pi_A)$  is the prior taken from the constant model and  $P(T_i^t | C^t)$  a distribution centered on  $C^t$  that expresses a proximity between  $C^t$  and  $T_i^t$  (concretely a Gaussian distribution centered on  $C^t$ ).

With this model, the distribution on eye movement can be computed with the following expression:

$$\begin{aligned} P(C^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_B) \\ \propto P(C^t | \pi_A) \\ \times \prod_{i=1}^N \sum_{T_i^t} \left[ \begin{array}{l} P(T_i^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_B) \\ \times P(T_i^t | C^t) \end{array} \right] \end{aligned}$$

In short, this model is the product between the prior on eye movement and each distribution on the targets convolved by a Gaussian distribution. This expression shows that this model is attracted towards the targets but without necessarily looking at one in particular as balance between the distributions on the targets can lead to a peak in some weighted sum of their locations.

*Uncertainty model* The behaviour of the preceding model is influenced by uncertainty insofar as the incentive to look near a given target is higher for a more certain location of this target. As for any Bayesian model, uncertainty is handled as part of the inference mechanism: as a mean to describe knowledge.

In this third model, we propose to include uncertainty as a variable to reason about: as the knowledge to be described. The rationale is simply that it is more efficient to gather information when and where it lacks than when and where there is less uncertainty.

Therefore, we introduce a new set of variables  $I_{(x,y)}^t \in [0, 1]$ , representing an index of the uncertainty at cell  $(x, y) \in \mathcal{G}$  at time  $t \in \llbracket 1, t_{max} \rrbracket$ . Any index can fit as long as we can correlate the value of this uncertainty index with the actual uncertainty.

To simplify, as we represent occupancy as binary variables, we choose our uncertainty indices to be equal to this probability of occupancy. The relation between this uncertainty index (probability distribution) and uncertainty is such as a probability near  $\frac{1}{2}$  represents a high uncertainty whereas a probability near 0 or 1 represent a low uncertainty. Other spaces can be chosen for these variables, such as entropy, but we keep the probability distribution to simplify our computations.

As above, this model is structured around a prior probability of motion which is filtered by these uncertainty variables so as to enhance probability of eye movement towards uncertain regions. The prior probability is the result of the preceding model  $\pi_B$ .<sup>3</sup>

The decomposition of this model is as follows:

$$P(C V M I | \pi_C) = \prod_{t=1}^{t_{max}} \left[ \begin{array}{l} P(V^t M^t | \pi_C) \\ \times P(C^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_B) \\ \times \prod_{(x,y) \in \mathcal{G}} P(I_{(x,y)}^t | C^t \pi_C) \end{array} \right]$$

where:

- $P(V^t M^t | \pi_C)$  is an arbitrary prior that is not used in the inference,
- $P(C^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_B)$  is the result of the previous model,
- $P(I_{(x,y)}^t | C^t \pi_C)$  is a beta distribution that expresses that for a given eye movement proposal  $C^t$ ,  $I_{C^t}^t$  is more likely near  $\frac{1}{2}$  and distribution on  $I_{(x,y)}^t$  for  $(x, y) \neq C^t$  is uniform.

This model computes the posterior probability distribution on next eye movement using the following expression:

$$P(C^t | V^{1 \rightarrow t} M^{1 \rightarrow t} I^{1 \rightarrow t} \pi_C) \propto P(C^t | V^{1 \rightarrow t} M^{1 \rightarrow t} \pi_B) \times P(I_{C^t}^t | C^t \pi_C)$$

where:

$$\forall (x, y), t \in \mathcal{G} \times \llbracket 1, t_{max} \rrbracket, \\ I_{(x,y)}^t = P(O_{(x,y)}^t | V^{1 \rightarrow t} M^{1 \rightarrow t})$$

as computed by equation 1.

This model filters the eye movement distribution computed by the second model, in order to enhance the probability distribution in the locations of high uncertainty.

<sup>3</sup> This is a matter of presentation of the model. The complete expression of  $\pi_C$  can be written without reference to model  $\pi_B$  but the addition of uncertainty would be less clear.

### 3 Results

The output of our models is a probability distribution over the eye position at each timestep. For such complex objects, there is no significance tests or sensitivity analysis and the comparison is done using their respective likelihood. However the likelihood is highly dependent on the size of the data set. Therefore we first introduce a comparison method that does not depend on the size of the data set. Then we present their results and comment them with respect to the specific behaviour of each model. Finally, we illustrate the main differences between the various models by giving examples of specific situations.

#### 3.1 Comparison method

The decision models compute a probability distribution over the possible eye movements at one moment, based on past observations and their respective hypotheses (figure 4). We can therefore compute, for each model, the probability of the actual eye movements recorded from subjects in a given situation, as well as the probability of the whole set of recordings with an additional independency assumption.

Probability values in themselves are not really significant as, when the possibilities are numerous, they tend to be very small. However, their comparison across models (which share the same number of possibilities) indicates which model is a better predictor of the recorded eye movements. This process is known as *Maximum Likelihood* method.

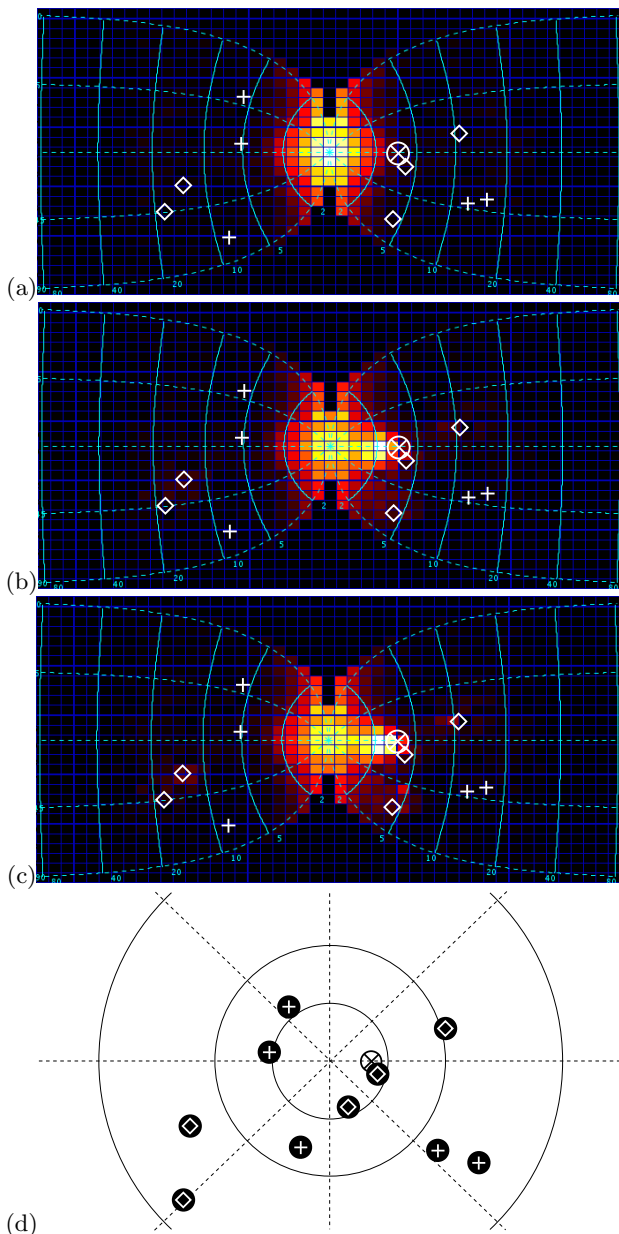
However, except in very special cases, the likelihood of a model would decrease exponentially toward zero, and the likelihood ratio between two models will diverge or converge exponentially toward zero with the number of trials. Therefore, we compare our decision models using the geometric mean of the likelihood of the observed eye movements over each trial. The geometric mean allows to be a substitute for the complete likelihood, as it is its  $N$ th root where  $N$  is the total number of trial, while providing a measure converging to a non-zero value as the number of trial grows.

More precisely, let  $c_n^t$  be the  $t$ th eye movement recorded during trial  $n$ . The likelihood of a model  $\pi$  for trial  $n$  is:

$$\prod_{t=1}^{t_{max}} P([C^t = c_n^{t+1}] | v_n^{1 \rightarrow t} c_n^{1 \rightarrow t} \pi)$$

The global likelihood of model  $\pi$  is:

$$\prod_{n=1}^N \prod_{t=1}^{t_{max}} P([C^t = c_n^{t+1}] | v_n^{1 \rightarrow t} c_n^{1 \rightarrow t} \pi)$$



**Fig. 4** Example of probability distributions computed by each decision model in the same configuration. The two halves of the representations are drawn side by side. The plain cyan lines are the iso-eccentricities and the cyan dotted lines are the iso-directions. The color of the cell indicates the probability of the associated eye movement: a dark cell for a low probability and a white cell for a high probability for the eye movement toward this cell.  $\diamond$ : position of a target;  $+$ : position of a distractor;  $\otimes$ : next eye displacement. Panel (a) is the probability distribution of constant model. Panel (b) shows the probability distribution for the target model that shows a preference for the targets. Panel (c) shows the probability distribution for the uncertainty model that highlights some of the targets. Panel (d) shows the position of the targets and distractors in the visual field. Note that the probability distributions for model (c) favors the next eye movement.

Finally we define our measure  $\mu$  to be the geometric mean of the likelihood over all the trials:

$$\mu(\pi) = \sqrt[N]{\prod_{n=1}^N \prod_{t=1}^{t_{max}} P([C^t = c_n^{t+1}] | v_n^{1 \rightarrow t} c_n^{1 \rightarrow t} \pi)} \quad (3)$$

### 3.2 Results and analysis

The data set is gathered from 11 subjects with 110 trials each for a total of 1210 trials (Tanner et al 2007). Each trial was regularly discretized in time in  $t_{max} = 24$  observations (with a timestep of 200ms) for a grand total of 29040 data points. The eye movement variable  $M^t$  is build from the difference in gaze position between two successive timesteps. Part of the data set (124 random trials) was used to determine the parameters of the various models and the results are computed on the remaining  $N = 1089$  trials.

Constant	Target	Uncertainty	Model
1	280	320	Constant
$3.5 \times 10^{-3}$	1	1.14	Target
$3.1 \times 10^{-3}$	0.87	1	Uncertainty

**Table 1** Ratio of the measures for each pair of models.

Table 1 presents the ratio of the measure for each pair of our three decision models computed for this data set. It shows that the model which generates motion with the empiric probability distribution but without the representation layer is far less probable than the other two (by respectively a factor 280 and 320). This shows that, as expected, the representation layer is useful in deciding the next eye movement.

Table 1 further shows that the model taking explicitly into account uncertainty is better than the model that does not by 14%. This is in favor of our hypothesis that taking explicitly into account uncertainty is helpful in deciding the next eye movement.

As explained above, the choice of the geometric mean prevents the measure to converge toward zero and prevents their ratios to raise exponentially as the number of trials grows. In our case, the likelihood ratio between the model with explicit uncertainty and the one without is  $4.9 \times 10^{63}$ . With half the trials, this likelihood ratio is the square root, that is only  $7.0 \times 10^{31}$ . This shows that the likelihood ratio is indeed not a stable measure with respect to the number of trials. We preferred a stable measure in order to have a more meaningful value.

### 3.3 Typical situations

These results show a global agreement of the model with the actual eye movements of the human participants.

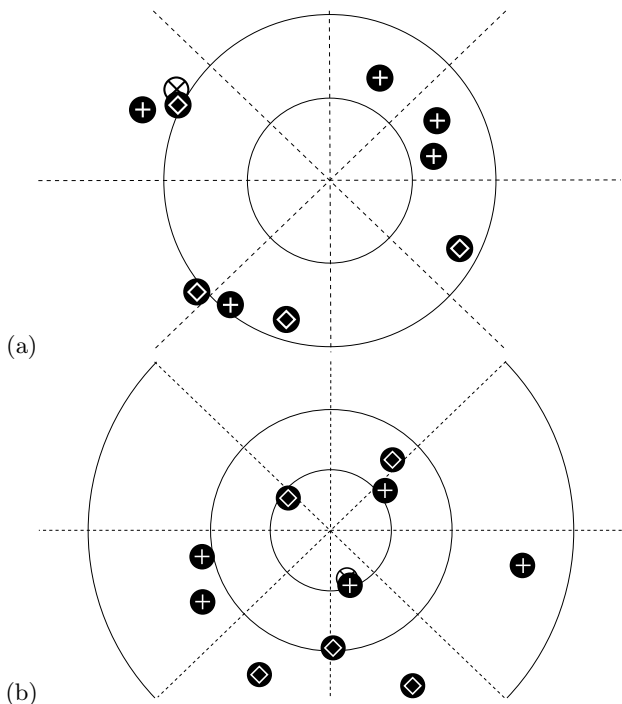


However, there are some configurations where the models can have different relative performances. The analysis of such examples can shed a light on the behaviour of the various decision models we proposed.

*Examples where  $\pi_C$  is better than  $\pi_B$*  The global result shows that it is better to take into account uncertainty explicitly for the choice of the eye movement. We can further investigate by looking at the frames where the difference in the likelihood is greatest.

We isolated two different categories of configurations where model  $\pi_C$  was especially better than model  $\pi_B$ , exemplified in figure 5. The first category consists in scenes where a target and a distractor are in a close vicinity and the eye movement of the participant is around those objects (Fig. 5a). In these case, the target model is simply attracted by the target whereas the uncertainty model is, in addition, attracted by both objects due to their uncertainty.

The second category consists in occurrences of an eye movement towards a distractor (see Fig. 5b). In this case, the target model has no incentive for looking at this location whereas there is always some uncertainty to investigate for model  $\pi_C$ .



**Fig. 5** Examples of eye movements better predicted by model  $\pi_C$  than model  $\pi_B$ . The scene is presented in an eye centered reference frame.  $\diamond$ : position of a target;  $+$ : position of a distractor;  $\otimes$ : next eye displacement. (a) The actual eye movement occurs towards both a target and a distractor. (b) The actual eye movement occurs towards an isolated distractor.

*Examples where  $\pi_B$  is better than  $\pi_C$*  Even if the global results are in favor of the model with explicit uncertainty, there are cases where the target model better predicts the eye movements. This happens mainly when the eye movements happen in the middle of several targets but not on a particular one (example Fig. 6a). In this case, the fusion on the targets operated by model  $\pi_B$  can present a maximum in a center of mass of the targets, whereas the absence of objects – and therefore the low uncertainty – will lower the probability of this particular eye movement by model  $\pi_C$ .

Fig. 6b illustrates a second interesting case. The eye movement occurs in between a target and a distractor. However, the occupancy grid at that time (Fig. 6c) shows that the target is moving and the eye movement is near the previous position of the target shown by a peak of occupancy in the corresponding cell. Therefore the eye movement is near the representation of the target. On the other hand, there is also a great patch near the center of the visual field with a moderate level of uncertainty where, consequently, model  $\pi_C$  predicts a high probability of eye movement.

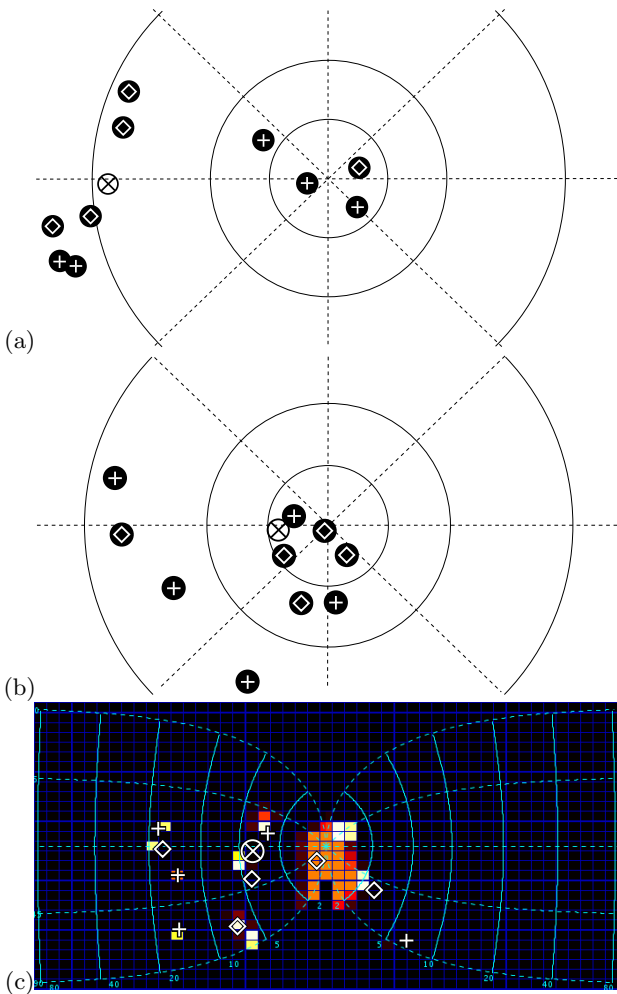
*Examples where  $\pi_A$  is better than  $\pi_B$  or  $\pi_C$*  Finally, the best model can be the constant one for some particular configurations and movements. This occurs mostly for fixations that are not directed to objects (for example Fig. 7a). Indeed model  $\pi_A$  is simply the global distribution of eye movements that are mostly of low amplitude (see Fig. 4a) and the other models are mostly attracted to targets or the uncertainty attached to objects.

Fig. 7b shows another occurrence of this situation with a group of target on the right towards which the other models predict a high probability of movement. It happens that, on the next frame, shown Fig. 7c, for which the situation is similar, the participant looked towards this group of targets, as predicted by both models  $\pi_B$  and  $\pi_C$ .

## 4 Conclusion and discussion

As a conclusion, we propose a Bayesian model with two parts: a representation of the visual scene, and a decision model based on the state of the representation. The representation both tracks the occupancy of the visual scene as well as the locations of the targets. Based on this representation, we tested several decision models and we have shown that the model that takes explicitly into account the uncertainty better fitted the eye movements recorded from subjects participating a psychophysics experiment.

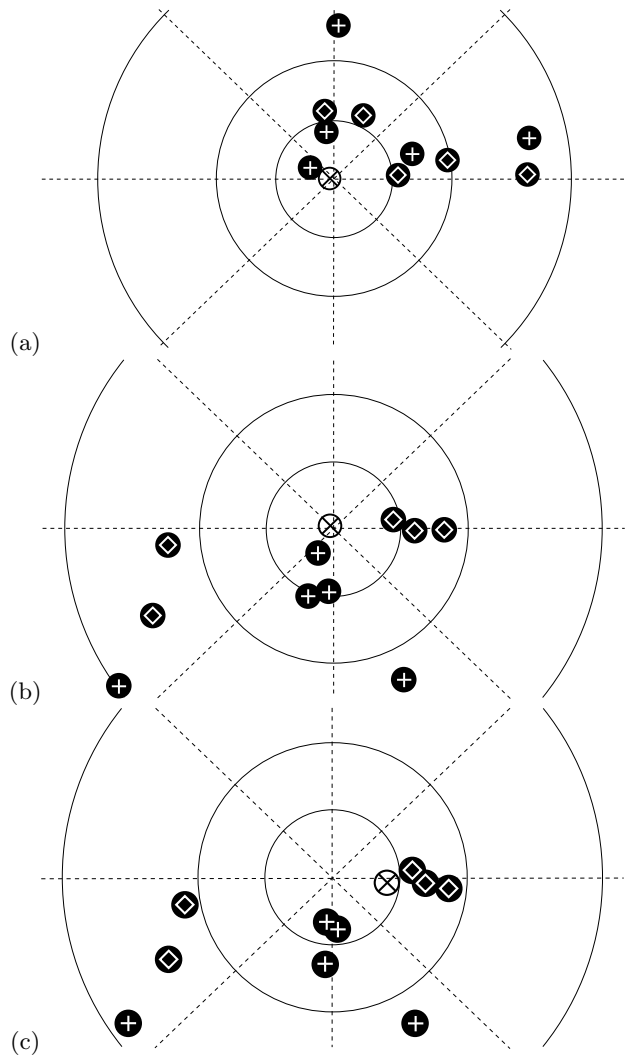
In addition, the eye movement frequency shows that, most of the times, the eye movements are of low amplitude, indicating either fixation or slow pursuit of an object. In these cases, the constant model has a likelihood comparable with or even sometimes greater than



**Fig. 6** Examples of eye movements better predicted by model  $\pi_B$  than model  $\pi_C$ . The scene is presented in an eye centered reference frame.  $\diamond$ : position of a target;  $+$ : position of a distractor;  $\otimes$ : next eye displacement. (a) The actual eye movement occurs in between several targets. (b) The actual eye movement occurs towards an isolated distractor. (c) Occupancy grid for the same configuration depicted in (b) showing the eye movement is near the past location of the target.

the other two. Thus the difference is due to the saccadic events, when the target and uncertainty model have a good likelihood contrary to the constant one which assigns a lower probability as the eccentricity grows. The difference between the target model and the uncertainty model, on the other hand is due to the filtering of the eye movements distribution from the target model by the uncertainty. The difference is less important than for the constant model as the uncertainty associated to the targets are often similar (isolated targets with comparable movement profiles). It could be interesting to enrich the stimuli in order to manipulate uncertainty more precisely.

The stimulus is adapted from the classical MOT task used primarily to study attention. Our model uses a set of variables to track the position of the targets. This set



**Fig. 7** Examples of eye movements better predicted by model  $\pi_A$  than models  $\pi_B$  or  $\pi_C$ . The scene is presented in an eye centered reference frame.  $\diamond$ : position of a target;  $+$ : position of a distractor;  $\otimes$ : next eye displacement. (a) The actual eye movement is a fixation without object. (b) The actual eye movement is also a fixation although there is a group of targets on the right. (c) Situation following (b) where the eye movement is towards the group of targets.

of variable is fixed and finite, which means our model can only track as much targets as its number of target position variables (5). The human subjects, however, are also informed about the number of targets in the instructions. Experimental data suggest that Human performance drops if the number of target gets too high. For the particular experimental design we used, the maximum number of targets consistently tracked was 5, which justifies our choice of the number of target variables. Other experimental studies suggest that this maximum number of target is not fixed and seems to depend on factors such as speed and spacing of the objects (Alvarez and Franconeri 2007). In addition, each of our target variables cover the whole visual field (encoded in the log-

complex mapping) although there are works indicating that some representation capacities are separated across the hemifields (Alvarez and Cavanagh 2005). It could be interesting to test this in our model with a set of target variables for the left part and another for the right part. However, due both to eye movements and targets movements, the targets sometimes change side, implying some additional mechanism of communication between these variables.

Finally, one of the main feature of our model is to place all computations and representation in the log-complex mapping found in the neurophysiology of some retinotopic maps. Unexpectedly, we found in the psychophysical data that the distribution of the objects positions is quite uniform in the logcomplex mapping. This suggests a particular strategy for the eye movements. One interpretation could be that the eye movements are chosen in order to maximize the use of the representation: that is, so that the objects are uniformly distributed in this representation. This seems to be an indirect confirmation that eye movements are governed by structures using this particular mapping.

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## A Experimental protocol

This experiment is an adaptation of the classical Multiple Object Tracking paradigm from Pylyshyn and Storm (1988) (see Fig. 3) but with eye movements. In the original task, participants were asked to keep track of a given number of targets among identical distractors as they all move independently on the screen. Participants had to keep their gaze at a fixating point located on the center of the screen. Therefore the targets will occasionally be located in the periphery of the visual field, in the low resolution areas of the visual field. Therefore we expect eye movements to occur in order to keep track of targets.

### A.1 Material and Methods

*Participants* Eleven subjects participated in the experiment with normal or corrected vision. Each session consists of 110 trials.

*Apparatus* The stimulus is presented on a calibrated 21" Sony CPD-500 CRT monitor with a refresh rate of 100 Hz and a resolution of  $1024 \times 768$ . Participants are positioned in front of the monitor at a distance of 65 cm; at this distance

the display subtended a visual angle of  $33^\circ$  by  $25^\circ$ . A chin rest ensures that no head movement occurs during the experimental session. All experimental sessions are performed in a darkened, sound attenuated room. Eye movements are recorded by an eye tracker system (EyeLink II, SR Research Ltd.) with a sampling rate of 250 Hz and an accuracy of ca.  $0.3^\circ$ . The model was simulated offline with a timestep of 200 ms using the difference in eye position between two timesteps. No analysis of saccades, micro-saccades, pursuit or fixation was needed in this respect.

### A.2 Procedure

The display consists of ten identical objects, each one a white circle subtending  $1^\circ$  of visual angle, with a luminance of  $90 \text{ cd/m}^2$  against a black background, in a room illuminated with diffuse D65 light ( $70 \text{ cd/m}^2$ ).

Targets and distractors are identical with the exception of the initial phase in the beginning of each trial. In this phase, five targets are cued by a series of three flashes, with a total duration of 1080 ms. After this initial phase, all objects begin to move in different directions, chosen from among 8 directions of the compass with a mean velocity of  $5.1^\circ$  per second. The objects have random initial locations, directions and speeds during trials but are constrained to keep a minimum distance of  $1.5^\circ$  (Pylyshyn and Storm 1988).

Trials last 5 seconds and on the end of each trial participants are asked to select targets with a mouse.

More details can be found in the description of experiment A in (Tanner, in preparation).

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## B Dynamic models

### B.1 Dynamic object model

This dynamic model provides the transition probability distribution  $P(O_{(x,y)}^t | M^t O^{t-1})$  that governs the evolution of the grid with the remapping capability. In order to stress the issue of the logcomplex mapping, we explicitly refer to the visual coordinates  $(\rho, \theta)$  as well as the logcomplex coordinates  $(x, y)$ . We also consider coordinates  $(\rho, \theta)_{ant}$  and  $(x, y)_{ant}$  to denote coordinates at the previous time step. In the end, the decomposition is as follows:

$$\begin{aligned} & P((x, y)_{ant} | (\rho, \theta)_{ant} O_{(x,y)}^{t-1} M^t) \\ &= P((x, y))P(M^t)P(O_{(x,y)}^t | (\rho, \theta)) \\ & \quad \times P((\rho, \theta)_{ant} | (\rho, \theta) M^t)P((x, y)_{ant} | (\rho, \theta)_{ant}) \\ & \quad \times \prod_{(x', y')} P(O_{(x', y')}^{t-1} | O_{(x,y)}^t (x, y)_{ant}) \end{aligned}$$

where:

- $P((x, y))$  is an arbitrary unused distribution;
- $P(M^t)$  is an arbitrary unused distribution;
- $P(O_{(x,y)}^t)$  is a uniform distribution;
- $P((\rho, \theta) | (x, y))$  is a uniform distribution on the inverse image of the position  $(x, y)$  by the logcomplex mapping;
- $P((\rho, \theta)_{ant} | (\rho, \theta) M^t)$  is a Dirac distribution on the image of  $(\rho, \theta)$  by eye movement  $M^t$ ;
- $P((x, y)_{ant} | (\rho, \theta)_{ant})$  is a Dirac distribution on the cell corresponding to position  $(\rho, \theta)_{ant}$ ;

- $P(O_{(x',y')}^{t-1} | O_{(x,y)}^t (x^{-1}, y^{-1}))$  is a transition matrix that states there is a great probability to keep the same occupancy if  $(x', y') = (x, y)_{ant}$ , and is a uniform distribution otherwise.

This model is used to compute the question  $P(O_{(x,y)}^t | M^t O^{t-1})$  using the following expression:

$$P(O_{(x,y)}^t | O^{t-1} M^t) \\ \propto \sum_{(\rho, \theta)} P((\rho, \theta) | (x, y)) P(O_{(\hat{x}, \hat{y})}^{t-1} | O_{(x,y)}^t (\hat{x}, \hat{y}))$$

where  $(\hat{x}, \hat{y})$  are the coordinates of the cell corresponding to the image of  $(\rho, \theta)$  by eye motion  $M^t$ .

This summation can be implemented by sampling the distribution  $P((\rho, \theta) | (x, y))$ .

## B.2 Dynamic target model

This dynamic target model is common to every target and combines both the prediction of the position of the target based only on eye movement (remapping) and the update of this position according to the occupancy grid. It provides the distribution  $P(T_i^t | T_i^{t-1} O^t M^t)$  used in the representation model.

The decomposition is as follows:

$$P(T_i^t | T_i^{t-1} (\rho, \theta) (\rho, \theta)_{ant} M^t O^t) \\ = P(T_i^t) P(M^t) P((\rho, \theta) | T_i^t) \\ \times P((\rho, \theta)_{ant} | (\rho, \theta) M^t) P(T_i^{t-1} | (\rho, \theta)_{ant}) \\ \times \prod_{(x,y)} P(O_{(x,y)}^t | T_i^t)$$

where:

- $P(T_i^t)$  is a uniform distribution;
- $P(M^t)$ : is an arbitrary unused distribution;
- $P((\rho, \theta) | T_i^t)$  is a uniform distribution on the inverse image of the position  $T_i^t$  by the logcomplex mapping;
- $P((\rho^{-1}, \theta^{-1}) | (\rho, \theta) M^t)$  is Dirac distribution on the image of  $(\rho, \theta)$  by eye movement  $M^t$ ;
- $P(T_i^{t-1} | (\rho, \theta)_{ant})$  is a Dirac on the cell corresponding to position  $(\rho, \theta)_{ant}$ ;
- $P(O_{(x,y)}^t | T_i^t)$  states that it is more probable to have an occupied cell in a neighborhood of  $T_i^t$ , and that it is uniform elsewhere.

This model is used to compute the question  $P(T_i^t | T_i^{t-1} O^t M^t)$  with the following expression:

$$P(T_i^t | T_i^{t-1} M^t O^t) \\ \propto |\mathcal{E}(T_i^{t-1}, M^t)| \prod_{(x,y)} P(O_{(x,y)}^t | T_i^t)$$

where  $|\mathcal{E}(T_i^{t-1}, M^t)|$  is the size of the set of the polar positions  $(\rho, \theta)$  that are in relation with  $T_i^{t-1}$  by the eye movement  $M^t$ . This set can be obtained by sampling like in the dynamic model.

## C Implementation details

The models presented are implemented in the Java language. In all the examples, the grid  $\mathcal{G}$  is composed of  $24 \times 29$  cells for each hemifield and we used a timestep of 200 ms for the representation and decision models.

Additionally, some of the probability distributions described as factors in the decompositions are parametric forms that need precise values to be involved in actual computations. We explored the parametrical space and evaluated each parameter set with our measure computed on a subset of the experimental data.

Finally, in the representation model, the observation model  $P(V_{(x,y)}^t | O_{(x,y)}^t)$  is a  $2 \times 2$  matrix with value 0.9 on the diagonal and 0.1 elsewhere

$$\begin{pmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{pmatrix}.$$

The transition matrix of the dynamic model is

$$\begin{pmatrix} 0.95 & 0.1 \\ 0.05 & 0.9 \end{pmatrix}.$$

The target observation model  $P(O_{(x,y)}^t | T_i^t)$  is of the form  $0.5 + \frac{0.25}{1 + \left(\frac{d((x,y), T_i^t)}{0.02}\right)^2}$  for an occupied cell and  $0.5 -$

$\frac{0.25}{1 + \left(\frac{d((x,y), T_i^t)}{0.02}\right)^2}$  otherwise with  $d((x,y), T_i^t)$  the distance between cell  $(x, y)$  and position  $T_i^t$  in mm. The target fusion model  $P(T_i^t | C^t)$  is a mixture between a Gaussian and a

uniform distribution:  $\propto 0.25 + \exp -\frac{d(T_i^t, C^t)^2}{0.25}$ . In the uncertainty decision model, the uncertainty fusion distribution  $P(I_{(x,y)}^t | C^t \pi_C)$  is a symmetrical beta distribution with parameter 0.075.

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