Anticipatory Models in Gaze Control: A Developmental Model*

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Abstract

Infants gradually learn to predict the motion of moving targets and change from a strategy that mainly depends on saccades to one that depends on anticipatory control of smooth pursuit. A model is described that combines three types of mechanisms for gaze control that develops in a way similar to infants. Initially, gaze control is purely reactive, but as the anticipatory models become more accurate, the gain of the pursuit will increase and lead to a larger fraction of smooth eye movements. Finally, a third system learns to predict changes in target motion which will lead to fast retuning of the parameters in the anticipatory model.

1 Introduction

To engage in a continuous interaction with a dynamic world, it is essential to anticipate how the world will change to select and control actions depending, not on the past, but on the future. One of the earliest interactions to develop in infants is the ability to look at moving objects. Smooth pursuit occurs when the eyes track a moving target with a continuous motion, which ideally is centered directly on the target and makes the image of the target stationary on the retina. Smooth pursuit is complicated by the fact that the initial visual processing in the human brain delays the stimulus by approximately 100 ms before it reaches the visual cortex (Wells & Barnes, 1998, Fukushima et al., 2002). If smooth pursuit movements were solely controlled by the position error on the retina, the eye would constantly lag a moving target.

To overcome this problem, the brain makes use of prediction (Deno et al., 1995, Mehta & Schaal, 2002, Poliakoff, Collins & Barnes, 2004). Because eye control is based on predicted target location rather than the actual target position which is not yet known, it is possible for the gaze to overshoot when the target disappears unexpectedly or changes direction. This does not happen when the disappearance of the target is controlled by the subject, for example by a button (Stork, Neggers & Müsseler, 2002). In this case, the gaze velocity slows down before the target disappears which shows that their expectations control the velocity of the smooth pursuit. Smooth pursuit movements cannot normally be generated without a moving stimulus, except that it can appear a short moment before a target is expected to appear (Poliakoff, Collins & Barnes, 2005, Wells & Barnes, 1998). Subjects can learn to anticipate the velocity a target will have when it appears, and in the case of several targets, subjects can produce predictive eye movements of approariate velocity when one of the targets is cued (Poliakoff, Collins & Barnes, 2004).

Infants as young as one month can exhibit smooth pursuit, but only at the speed of 10 degrees/s or less and with low gain (Roucoux et al., 1983). A three month old infant does not follow if a target abruptly changes its direction of movement. Instead it continues in the original direction for a quarter of a second before adjusting its eye movements (Aguiar & Bailargeon, 1999). However, at five months of age, the infant learns the abrupt turn and its lag is reduced. The ability to smoothly track a target thus develops very rapidly, and at five month of age this ability approaches that of adults (von Hofsten & Rosander 1997).

Before the infant can use smooth pursuit, it follows moving targets using small saccade movements that rapidly move the gaze from one position to another (Dayton & Jones, 1964). As the smooth pursuit system develops, these saccades become less frequent, but are still used to catch up if the lag becomes too large.

Of particular interest is how infants behave when the target disappears, for example behind an occluder. According to Piaget (1937), the child is able to predict that a train that disappears at one end of a tunnel will appear at the other end. This can either be explained by a tracking mechanism that

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continues to track the motion of the train when it has disappeared, or as form of event learning where the child learns to predict that the disappearing train predicts the subsequent reappearance of the train. There exits evidence for both types of mechanisms. For example, Wentworth and Haith (1998) found that three-month-old infants could learn spatiotemporal expectations. Other researchers have mainly studied the ability of infants to smoothly track a moving target using predictive models of the motion (von Hofsten & Rosander & 1997, Rosander & von Hofsten, 2004).

Contrary to earlier speculations, infants do not continue to track an occluded objects with smooth pursuit. Instead the tracking stops and one or two saccades are made to the other side of the occluder (Rosander & von Hofsten, 2004). These saccades are made to anticipate when the object reappear – not when it disappears. Infants that are 7-9 weeks old continue to look at the edge of the occluder where the object disappears for 1 second before finding it again (Rosander & von Hofsten, 2004). Infants that are 12 weeks old move their eyes as soon as the target becomes visible again. This delay decreases with each trial which indicates that the infant starts to anticipate where the objects will reappear. Some of these effects have been seen in younger infant as well, but they have not been reliable. It is possible that the younger infant would have performed better if the object was made invisible instead of occluded since the occluder distracts attention from the target (Jonsson & von Hofsten 2003).

Given these interesting properties, the control of gaze is an ideal domain to study the mechanisms behind anticipation, the learning of dynamic interaction and event learning. In the following sections, we present a computational model of how gaze control develops and how mechanisms for dynamic control interacts with mechanisms for event learning.

2 Coping with Delayed Feedback

What are the requirements of a system that needs to predict the motion of a visual target? Consider a system that attempts to predict the position of a target object based on a sequence of its previous positions. Such a system should learn a function from a number of observed positions $p(t-n), \ldots, p(t-1)$ to the estimated position $\hat{p}(t)$ at time t. Any of a number of learning algorithms could learn such a function by minimizing the prediction error $e(t) = p(t) - \hat{p}(t)$. The learned function constitutes an anticipatory model of the target motion.

We now add the constraint that the perception of the target, including its localization, takes τ time units. In this case the problem translates to estimating $\hat{p}(t)$ from $p(t-n), \ldots, p(t-\tau)$, since the rest of the sequence is not yet available. In addition, this means that the system only has access to the prediction error $e(t)$ after τ additional time steps, that is, learning has to be set off until the error can be calculated and the estimate of $\hat{p}(t)$ has to be remembered until time $t+\tau$ when the actual target location $p(t)$ becomes available.

The important point here is that a system of this kind will never have access to the current position of the target until after a delay. Any action that is directed toward the current target position will thus have to depend on the predicted location rather than the actual one. This is further complicated by the fact that any action directed toward the predicted location will also take some time to execute. For example, if an action is performed with constant reaction time ρ, an action directed at $\hat{p}(t)$ at time t will miss the target, since once the action has been performed the target will be at position $p(t+\rho)$. Consequently, the system needs to anticipate the target position $\hat{p}(t+\rho)$ already at time t when the action is initiated.

In summary, the system needs to keep track of the target at three different times. The first consists of the currently observed set of positions $p(t-n), \ldots, p(t-\tau)$ that can be called the *perceived now*. The second is the *anticipated now*, that is, $\hat{p}(t)$. This is the actual position where the target currently is, but this is not yet accessible. Finally, any action must be controlled by the *anticipated future*, that is, $\hat{p}(t+\rho)$.

Although this looks like a very complicated way to handle time, unless the delays τ and ρ are negligible, the use of some form of prediction is unavoidable. The delays in the human brain are long enough to necessitate anticipatory models and this has important consequences for how we learn to pursue a moving object with our eyes.

3 A Model of Visual Control and Development

There are three ways in which the direction of gaze can be controlled that can be considered three different pathways from sensation to motor control. These three pathways are summarized in the computational model shown in Fig. 1.

The reactive saccade pathway generates saccades based on the location of salient features in the image that are outside the focal region. The anticipatory pursuit pathway consists of a target detections system together with a predictive model and a control system that is used to generate smooth pursuit movements. Finally, the third pathway consists of an event predictor that can learn arbitrary relations between visual events.

The selection between the different pathways is similar to an earlier design that has been implemented in a stereo vision head (Balkenius & Kopp, 1996). The visual field is divided into three regions and different control strategies are used depending on in which region the target is located. In the focal region, gaze is controlled by the pursuit pathway by a controller that handles both smooth pursuit and fixation, which is in line with evidence that the same mechanism is used for these two behaviors (Smeets & Bekkering, 2000). When the target is in the intermediate and peripheral regions, different types of saccades are generated instead by the saccade pathway. When no target is visible or when it is expected to change its movement, the event prediction pathway can move the gaze to a location where a target may appear or change the parameters of the target predictor to anticipate the changed movement.

The direction of gaze is updated according to $g(t+1) = g(t) + v(t) + s(t) + a(t) + n(t)$, where $v(t)$ is the velocity from the pursuit pathway, $s(t)$ is the bursts from the saccade generator, $a(t)$ is a saccade generated by the event predictor pathway, and $n(t)$ is a noise term. For the sake of presentation, we will assume in the following that the model only needs to direct the gaze to the correct horizontal position of the target. All values can thus be assumed to be scalars.

3.1 The Reactive Saccade Pathway

The first pathway is controlled by a pre-attentive system that selects salient features or stimuli in the image and directs attention to them. This system is based on the model of pre-attentive processing introduced by Itti, Koch & Neibur (1998) and produces exogenous saccades. This part of the model consists of a number of simple filtering operations including the detection of oriented contrast, curvature, foreground elements, and motion (Balkenius, Eriksson & Åström, 2004). The resulting pre-attentive maps are added together to form a salience map from with the next target location is selected. The probability of selecting a region in the image is proportional to the salience of that region which is given by the salience map. In Fig. 1, the visual signal through the reactive saccade pathway is represented by the position of the target in retinal coordinates $r(t)$.

When the selected target location is sufficiently far away from the center of the eye, a saccade toward the target is generated by the saccade generator. In the *intermediate region* around the center, catch-up saccades are generated to tracked objects (cf. Smeets & Bekkering, 2000) and in the *peripheral region*, an orienting system is used to roughly direct attention in the direction of any transient event (Balkenius & Kopp, 1996).

When gaze is controlled solely by the saccade pathway, small saccades will be produced that track any salient stimulus in view. This behavior parallels that of the new-born infant for all but slowly moving targets (Lengyel, Weinacht, Charlier, Gottlob, 1998).

3.2 The Pursuit Pathway

The pursuit pathway uses a control system for target tracking similar to that of Shibata et al. (2001), where a forward-model is used to predict target velocity based on image-slip and gaze (Fukushima et al., 2002). Unlike the model of Shibata et al. (2001), all calculations are made with positions rather than velocities and velocities are only used implicitly as differences between locations. In this system, the prediction of target motion is separate from the motor control of the eyes, which seems to be the case also in the human gaze-control system. The prediction is made in world-centric coordinates while motor control is made in ego-centric coodinates. This is very important for the success of the system since learning of target motions should not interfere with the learning of eye control. This also makes target prediction immune to movements of the body.

The pursuit pathway consist of two main parts (see Fig. 1). One is used for target prediction and the second is used to control the smooth movements of the eye. There are also two modules that performs transformations between eye coordinates $g(t)$ and world coordinates $p(t)$. In the present model, these transformations are made by simply adding or subtracting the horizontal position for the eye from the target location in the eye. In a more general model, these transformations should allow any three-dimensional transformation. There is also a delay in the pathway from the eye position to the target predictor that matches that of the delay in the visual processing. Because of the delay within the visual system, the pursuit pathway operates on the delayed signal $p(t - \tau)$ as described in section 2.

The target predictor consists of a linear predictor which attempts to predict the current location of the target stimulus based on a number of target locations that are delayed by τ time steps.

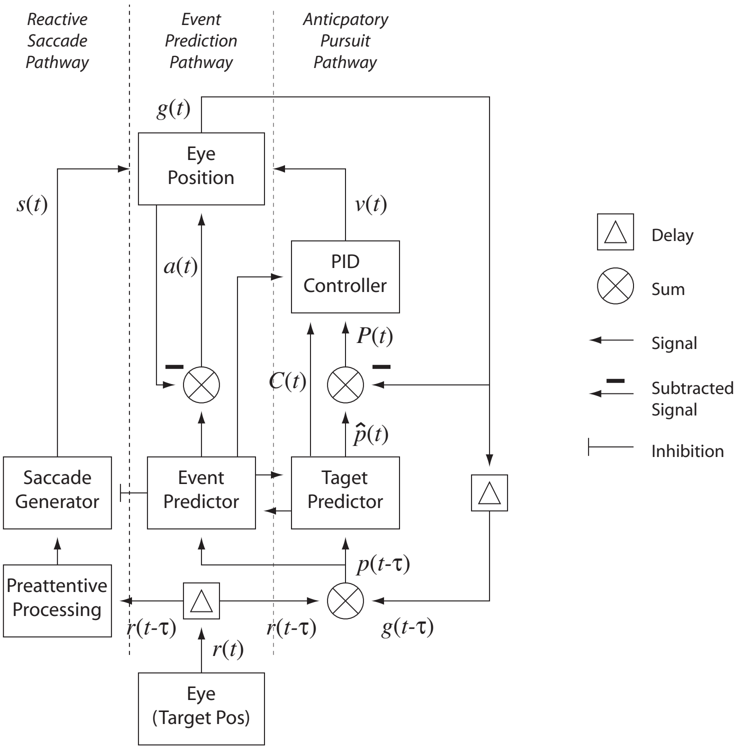

FIGURE 1: *The model consists of a number of interacting modules for different processes. The visual stimulus can control gaze through three different pathways: the reactive saccade pathway that directs attention to a salient stimulus; the event prediction pathway that direct attention to location where the target is predicted to appear; and the anticipatory pursuit pathway that controls smooth eye movements based on the predicted position of the target. See text for further explanation.*

$$\hat{p}(t+1) = \sum_{i=\tau}^{n} c_{i-\tau}(t) p(t-i).$$

The scalar coefficients c_i are learned on line based on the error of the prediction. Note that the subscripts of the coefficients indicates that they relates to signals that have been differently delayed while the argument t indicates that the coefficients change over time as a result of learning. Thus, at time t, we know the correct target location at time $t-\tau$ and can update the constants based on the prediction error $e(t-\tau)$. The weights of the predictor are updated according to the following equation,

$$c_i(t+1) = c_i(t) + \alpha e(t-\tau) p(t-i),$$

where α is the learning rate and e(t) the prediction error. As a consequence of this equation, the coefficients will change in a direction that makes the prediction error decrease. Note that the predictor is simultaneously operating in two different time frames as explained in section 2, one for learning, *the perceived now* where previous predictions can be compared with actual target positions, and one for prediction, *the anticipated now* where the actual target position is not yet accessible.

Finally, the uncertainty $U(t)$ of the prediction is calculated as an exponentially decaying average of the prediction error $e(t)$,

$$U(t+1) = (1-\beta)U(t) + \beta e(t-\tau).$$

The constant β controls the amount of decay. The value $U(t+1)$ is subsequently used to calculate the confidence of the prediction

$$C(t+1) = e^{-U(t+1)}.$$

PID Controller The eye control system uses a standard proportional-integral-derivative (PID) controller. This one of the simplest forms of control systems often used in technical applications. In such a controller, the control signal $v(t)$ is the sum of three different terms P, I and D,

$$v(t+1) = v(t) + C(t)\left[c_P P(t) + c_I I(t) + c_D D(t)\right],$$

where $P(t)$ is the error of the gaze position, $I(t)$ is the integral of the error over time, $I(t) = \sum_{i=0}^{t} P(i)$ and $D(t)$ is the differentiated error $D(t) = P(t) -$

$P(t-1)$. The values c_P, c_I, and c_D are parameters that define how much each type of error term contributes to the control signal. The three terms have different roles in controlling the speed of the eye. The proportional term $P(t)$ tries to immediately compensate for the error. The integral term $I(t)$ adds errors over time which makes the gaze eventually catch up with a moving target. Finally, the derivative term $D(t)$, helps the system cope with sudden changes in the target position. Although it would be possible to include learning of the parameters in the controller, this was not used in the current implementation.

The three control signal is multiplied with the confidence from the target predictor to model the development of smooth pursuit. The result will be that the gain of the controller depends on the confidence of the target prediction. As the model becomes more accurate, the gain will increase, and the complete system will gradually become more able to pursue a moving target. This is a critical aspect of the model as it could explain the transition in infants from tracking based on saccades to tracking based on smooth pursuit. By using the confidence of the prediction to set the gain of the controller the system is automatically shielded from moving the eye too fast and perhaps incorrectly before it has an accurate model of the way the target behaves. Once the prediction becomes better the gain will increase and the pursuit system will lock on to the target. As a consequence, the target will be in focus a larger fraction of the time and the number of saccades will decrease.

3.3 Event Prediction Pathway

The event prediction pathway contains one main module that detects events and forms associations between them. When this module predicts that the target will appear it will produce an endogenous saccade $a(t)$ to the expected location and simultaneously inhibit the saccade generator (Fig. 1).

An event is defined as any abrupt change in any variable within the system (cf. Prem et al., 2002). In the present model, we have included two signals that are used to detect events: the tracking error and the recognition of the target objects. Fast changes of the tracking error will thus be considered as an event as will the appearance or disappearance of the target. When an event occurs the type of event and corresponding location is saved so that it can potentially be correlated with other later events.

The anticipated changes in target motion and location are learned as associations between two events: $E_1 \rightarrow E_2$, where E_1 may be the disappearance of the target or the fact that the target reaches a certain location, and E_2 is the reappearance of the target or the expected new position of the target.

The learned associations does not only code that a target disappearing at a location $\langle x, y\rangle$ will appear at another $\langle x', y'\rangle$, but also the time between the two events Δt and the expected velocity when the target reappears v (Poliakoff, Collins & Barnes, 2004): $\langle x, y\rangle \rightarrow \langle x', y', \Delta t, v\rangle$.

This learning is driven by the rewarding property of the target, i. e. when the target appears it will generate a reward that will drive the learning of the event associations. This is consistent with the observation that all brain systems involved in the linking between visual stimulation and oculomotor behavior encode the expected value of the target (McCoy & Platt, 2005).

The anticipatory saccades constitute a form of adaptive switching control strategy, where the anticipatory saccade controller quickly sets the parameters of the smooth pursuit controller to immediately obtain good tracking performance (Huang & Lin, 2004). For example, if the target is first moving along a straight line with constant velocity, the target predictor will anticipate that this movement will continue and the eye will thus follow this line. However, if an even occurs that indicate that the target will change direction, it is necessary to reset the current prediction and instead predict the new target motion that is cued by the event. Evidence that arbitrary stimuli can be used to predict the appearance, time and velocity of a stimulus in adults comes from experiment by Barnes and Donelan (1999).

4 Results

The model was tested in an experiment that was similar to one reported by von Hofsten & Rosander (1997), with a target that moved back and fourth along a horizontal line. There was a 100 ms delay of the visual input. A new frame was processed every 20 ms to parallel the human visual bandwidth of approximately 50Hz. One cycle where the target moved back and fourth one time lasted for 5 second and the target moved over 60 degrees of the visual field from end to end.

The constants were set as $\alpha = 0.1$, $\tau = 5$, and $n = 7$. To be able to evaluate the target predictor after learning, the theoretical prediction coefficients c_i were calculated for three types of predictors: (A) a simple linear extrapolation of position based on the calculated velocity between the last two target positions and the known delay τ, (B) another linear predictor that averaged the last two estimated velocities, and (C) a prediction that also included the estimated acceleration of the target. As can be seen in Table 1, the theoretical model that takes acceleration into account gives the smallest error. However, when noise is added to each target location, the performance of this predictor deteriorates considerably. In this case, the predictor that averages over two velocity estimates gives the best result.

The target predictor was subsequently allowed to learn the prediction coefficients from observations of an sinusoidal motion along the horizontal line. When the predictor had learned the coefficients, they resembles predictor B, except that c_1 is not zero indicating that the current position is a weighed average between the last two target locations. The performance of this learned predictor is close to that of predictor B.

We also tested what the target predictor would learn if the amount of noise was increased. In this case, it is able to learn coefficients that results in a lower average error than any of the other predictors since it learns to essentially use the average of the last three target positions as the estimate. Although the error is reduced, the target estimation now lags the real target location and is no longer anticipatory.

These results show that a linear predictor can learn the appropriate coefficients to make anticipatory estimates of the target location. These coefficients favor an estimation that averages over several target locations and will thus only become anticipatory when the target locations are sufficiently reliable. The learned predictive model is a compromise between limiting the sensitivity to noise and making an accurate prediction.

The development of the pursuit system was simulated for the model when it continuously viewed a sinusoidal movement. As the confidence of the prediction increased, so did the gain of the smooth pursuit system. The parameters were set as in the previous simulations. The target moved either according to a sinusoidal path or in a triangular way (Fig. 2).

Fig. 2 shows the development of smooth pursuit from initial saccadic tracking to the final model based tracking. Even when a predictive model is used to control the gaze, there is still a small overshoot that is casued by the abrupt change of direction in the triangular motion. This overshoot almost completely disappears when the event detection system is added. In this case, the predicted target location at the end of the envelope triggers an event that will associate to a new velocity and direction of the target.

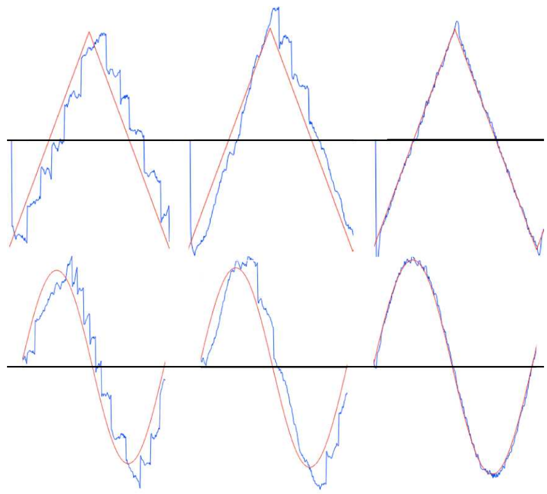

FIGURE 2: *The development of smooth pursuit in the model while tracking a sinusoidal or triangular target motion. Left: No smooth pursuit. Middle. An intermediate stage. Right: Fully developed predictive smooth pursuit. The difference between the tracking motions is mainly a result of an increased gain of smooth pursuit.*

5 Discussion

The model shows how it is possible to combine three different types of gaze control: reactive, continuous model based, and event driven control using a form of switching control that depends on both the location of the target on the retina and on the certainty of the the predicted motion of the target. The behavior of the model shares many properties with the gaze control of infants and develops through similar stages.

The reactive part of the model produces exogenous saccades to salient targets but is not able to predict the movement of the selected target. On its own, this subsystem will be able to track a moving target using small saccades that always lags the real position of the target (cf. Itti, Koch & Niebur, 1998).

In contrast, the pursuit system anticipates the continuous behavior of the target and is able to look on to its movement. If the model is correct, this will allow the gaze to be directly centered on the target while it is moving. The gain of this subsystem depends on the accuracy of the prediction. Smooth pursuit will thus become more frequent as the model becomes more accurate. This will automatically result in a gradual development from a primarily saccade-based gaze control strategy to one that depends increasingly on smooth pursuit that parallels the development of infant gaze control (von Hofsten & Rosander, 1997, Lengyel, et al., 1998, Richards & Holley, 1999, Rosander & von

Table 1: *Theoretical and learned prediction coefficients and the corresponding prediction errors with and without noise with a sinusoidally moving target. The noise was additive with a range from -10 to 10 degrees.*

Type	c_0	c_1	c_2	LMS Error	With Noise
A. Linear	6	0	-5	$2.0 \cdot 10^{-3}$	$3.3 \cdot 10^{-2}$
B. Averaged	3.5	0	-2.5	$2.2 \cdot 10^{-4}$	$1.8 \cdot 10^{-2}$
C. Acceleration	18.5	-30	12.5	$3.3 \cdot 10^{-5}$	$3.5 \cdot 10^{-1}$
Learned	3.2	0.33	-2.53	$2.4 \cdot 10^{-4}$	$1.9 \cdot 10^{-2}$
Lrn w noise	0.36	0.32	0.24	$5.3 \cdot 10^{-3}$	$5.3 \cdot 10^{-3}$

Hofsten, 2004). The model suggests that the transition from saccadic pursuit to smooth pursuit in infants is a result of a gradually developed ability to predict the behavior of moving targets. This implies that an infant should be able to use smooth pursuit to track a complex but known target motion, but not a simpler but novel target motion.

The final part of the model detects discrete events and forms predictions between them. Such an event can be the target disappearing or reappearing or a sudden change in motion. By learning relations between discrete events, it becomes possible for the model to use simple general continuous models for smooth pursuit while simultaneously being able to anticipate complex target behaviors. The ability to predict discrete events develops in infants as early as the second month of life (Haith, Hazan & Goodman, 1988), and if such expectations are allowed to influence the parameters of the target predictor, the continuous models do not need to be very complex.

The model makes the explicit prediction that visual tracking requires two complementary predictive systems: one that learns continuous models of target motion and one that learns discrete events that changes the motion of the target. An interesting question is the relative roles of the continuous target predictor model and the discrete event prediction system. The simulations show that the complexity of the predictive models that can be learned depends to a large extent on the amount of noise in the system. For example, if the noise increases, it is no longer possible to learn a model with acceleration. With even higher noise, the model loses its ability to predict and will simply average the previous positions to estimate the current location of the target. However, in the real world, the motion of a target object can often be very complex and noisy. Does this mean that an infant will not be able to learn to track such targets? On the contrary, the model suggests that the way to handle complex motion is through a second subsystem that detects events and directly changes the parameters of the target predictor.

The model also suggests that the different predictive models that an infant learns should operate in world coordinates. Although it is conceivable that ego-centric or eye-centric coordinates could be used for simple linear motion, this immediately becomes problematic if the observer is moving around in the world. In this case, it would be necessary to adjust the prediction for ego-motion which is just as complicated as using world coordinates in the first place. This prediction could be tested by investigating how ego-motion interact with smooth pursuit.

In the future, we want to further investigate how the system can learn and use several different models concurrently (cf. Wolpert et al., 2003) and how the task context can influence which model is used (Doya, et al., 2003, Balkenius & Winberg, 2004). This type of model may also form a basis for the study of the development of synchronization and imitation (Barnes & Donelan, 1999).

We also want to investigate the relation between this type of switching control and reinforcement learning and how the system can learn to generalize from previously learned scenes to new ones, which may eventually make it able to track moving objects perfectly on the first trial.

A limitation of the current model is that the association mechanism is very simplistic since it only associates two subsequent events with each other. It can not learn regularities over longer times if they are interrupted by other events. This limitation will be addressed in the future when a more advanced associative mechanism will be included in the model.

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