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Predictive Tracking Across Occlusions in The iCub Robot

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Abstract— **In humans the tracking of a visual moving target across occlusions is not made with continuous smooth pursuit. The tracking stops when the object is occluded and one or two saccades are made to the other side of the occluder to anticipate when and where the object reappears. This paper describes a methodology for the implementation of such a behavior in a robotic platform – the iCub. We use the RLS algorithm for the on-line estimation and prediction of the target trajectory and a vision based object tracker capable of detecting the occlusion and the reappearance of an object. This system demonstrates predictive ability for tracking across an occlusion with a biologically-plausible behavior.**

I. Introduction

The primate visual system is characterized by binocular visual fields and a space-variant resolution retina with a high-resolution fovea that offers considerable advantages for a detailed analysis of visual objects, together with effective visuo-motor control [1]. The space-variant resolution of the retina requires efficient eye movements for correct vision.

Two forms of eye movements — saccades and smooth pursuit — enable us to fixate the object on the fovea. Saccades are high-velocity gaze shifts that bring the image of an object of interest onto the fovea. Smooth pursuit occurs when the eyes track a moving target with a continuous motion, in order to minimize the image slip in the retina and make it perceptually stable. Smooth pursuit movements cannot normally be generated without a moving stimulus although they can start a short moment before the target is expected to appear [2]. 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[2][3]. In primates, with a constant velocity or a sinusoidal target motion, the smooth pursuit gain, i.e. the ratio of tracking velocity to target velocity, is almost 1.0 [4]. This cannot be achieved by a simple visual negative feedback controller due to the long delays (around 100 ms in the human brain), most of which are caused by visual information processing.

In the monkey brain, the neural pathway that mediates smooth-pursuit eye movements, described in [5], starts in the primary visual cortex (V1) and extends to the middle temporal area (MT) that serves as generic visual motion processor. It contributes to smooth pursuit measuring the target motion in retinal coordinates[6][7][8]. By contrast, the middle superior temporal area (MST) seems to contain the explicit representation of object motion in world centred coordinates [9]. Recent works [10] demonstrate that this area is responsible for target dynamics prediction. Cortical eye fields are also involved in smooth pursuit [11]; in particular the frontal eye field (FEF) can modulate the gain control [12][13][14] that determines how strongly pursuit will respond to a given motion stimulus.

When the pursued object is occluded, the smooth eye movements get effectively interrupted. Subjects switch gaze across the occluder, with saccades, to continue tracking [15]. This is valid for visual tracking in adults [16][17] and in infants[18]. Infants react differently from adults to occlusions of the object. Adults always predict the reappearance and their gaze arrives at the opposite side of the occluder slightly before the object. Infants can simply maintain a representation of the object motion while the object is occluded and shift gaze to the other side of the occluder when the conceived object is about to arrive there. In support of this alternative are the findings that object velocity is represented in the frontal eye field (FEF) of rhesus monkeys during the occlusion of a moving object [19].

An interesting paper about occlusions and eye movements is proposed by Zhang and colleagues [20]. They describe a real-time head tracking system, formulated as an active visual servo problem based on the integration of a saccade and a smooth pursuit process.

In this work a model of a predictive smooth pursuit is integrated with saccades to follow a moving target. A robotic implementation of this model is provided to track an object (a sphere) that has a sinusoidal dynamics with a centrally placed occluder. A method based on 3D particle filter is used to track the target, determine when it is occluded and detect its reappearance.

II. Smooth pursuit model

An important biologically plausible smooth pursuit controller has been proposed by Shibata [21]. This controller learns to predict the visual target velocity in head coordinates, based on fast on-line statistical learning of the target dynamics. In general, the model takes about five seconds to converge and it is slower than the human smooth pursuit system [21]. This model has been modified to improve its convergence speed by using a memory based

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internal model that stores the already seen target dynamics. Figure 1 shows the smooth pursuit model block schema. The Estimator State module generates the target velocity estimation according to equation 1 and computes position by integrating the velocity information. The state vector $\bar{\mathbf{x}}$ is used by the Predictor to compute the target velocity $\hat{\dot{x}}$ in the next time step. The Inverse Dynamics Controller generates the necessary torque force that allows the Eye Plant to reach the predicted velocity (equation 6). This controller corresponds to the low-level velocity controller of the robot. The control model consists in three subsystems: a RLS predictor mapped onto the MST, which receives the retinal slip, i.e. target velocity projected onto the retina, with delays, and predicts the current target motion; the inverse dynamics controller (IDC) of the oculomotor system, mapped onto the cerebellum and the brainstem; and the internal model that recognizes the already seen target dynamics and provides predictions that are used alternatively to the RLS predictor.

Since the brain cannot observe the target state vector $\boldsymbol{x} = [x\ \dot{x}]^T$ directly, the first part predicts the current target velocity $\hat{\dot{x}}$(t) from the delayed estimated target state $\bar{\boldsymbol{x}}(t - \Delta)$. This is calculated from the retinal slip information $\dot{e}(t)$ and the eye velocity $\dot{E}(t)$ as follows:

$$\bar{\dot{\mathrm{x}}}(\mathrm{t}-\Delta) = \dot{\mathrm{E}}(\mathrm{t}-\Delta) + \dot{\mathrm{e}}(\mathrm{t}-\Delta) \quad (1)$$

The estimated target position $\bar{x}(t - \Delta)$ is obtained by integrating $\bar{\dot{x}}(t - \Delta)$. According to neurophysiological studies (Kawawaki et al. 2006), the MST area predicts only the velocity information about the target dynamics. To predict the target velocity the model uses a second order linear system to represent the target dynamics:

$$\hat{\dot{x}}(\mathrm{t}) = \boldsymbol{w}^T\bar{\mathbf{x}}(t - \Delta) \quad (2)$$

where $\boldsymbol{w}$ represents the vector of regression parameters and $\hat{\dot{x}}$(t) is the predicted target velocity. A recursive least squares algorithm (RLS) [22]is employed for learning, because it is robust and it guarantees convergence. Originally, RLS requires the presence of a target output in the update rules, but the predictor can only utilize the retinal signals as the prediction error. Thus, the algorithm is modified as follows:

$$\mathbf{P}(t) = \frac{1}{\lambda}\left[\mathbf{P}(t - \Delta) - \frac{\mathbf{P}(t-\Delta)\boldsymbol{x}(t)\boldsymbol{x}(t)^T\mathbf{P}(t-\Delta)}{\lambda+\boldsymbol{x}(t)^T\mathbf{P}(t-\Delta)\boldsymbol{x}(t)}\right] \quad (3)$$

$$\mathbf{w}(t) = \mathbf{w}(t - \Delta) + \frac{\mathbf{P}(t)\boldsymbol{x}(t)}{\lambda+\boldsymbol{x}(t)^T\mathbf{P}(t)\boldsymbol{x}(t)}\dot{e}(t + 1) \quad (4)$$

$$\hat{y}(t) = \mathbf{w}(t)^T\mathbf{x}(t) \quad (5)$$

where $\mathbf{P}$ is the inverted covariance matrix of the input data, $\boldsymbol{x}$ is the input state and λ is the forgetting factor which lies in the [0, 1] interval. For λ = 1, no forgetting takes place, while for smaller values, the oldest values in the matrix $\mathbf{P}$ are exponentially forgotten. Essentially, the forgetting factor ensures that the prediction of RLS has an influence windows of about $1/(1 - \lambda)$ data points. This forgetting strategy also enables the predictor to be adaptive to the changes in the target dynamics. Another important element of (4) is that it explicitly shows the requirement for the time alignment of the predictor output and the error since the learning module cannot see at time *t*. Thus, all variables in (4) are delayed by one time step, which requires the storage of some variables for a short time in memory.

The second part of the Schaal and Shibata's model is based on theory and experiments showing that the cerebellum and brainstem together act as an inverse dynamics controller of the oculomotor plant [23][24].The model assumes that the IDC has the capability to cancel the dynamics of the eye plant, making it valid to write:

$$\dot{E}(t) = \hat{\dot{x}}(t) \quad (6)$$

In accordance with [25], the prediction in smooth pursuit movements is about 200 ms. In order to obtain a prediction of 200 ms, the model shown in figure 1 includes a delay block before the eye plant, so that the predictor must adapt its dynamics both to visual delay and eye plant dynamics.

The third part is based on the fact that there is a direct relationship between the angular frequency of the target dynamics and the final weights of the model, expressed in (4). Such values depend only on the angular frequency of the target dynamics and on the configuration of the system, being independent from the amplitude and the phase of the sinusoidal motion. A memory block (Internal Model) recognizes the target dynamics and it provides the correct weights values before the RLS algorithm. For this purpose, such weight values are stored in a neural network (MLP) for future presentation of learned target dynamics. This network has 10 neurons in the input layer, 25 neurons in the hidden layer and 2 neurons in output layer that correspond to the two regression parameters of RLS algorithm. It uses the non linear activation sigmoid function with backpropagation learning rule.

The neural network inputs are a sample series of initial velocity values of the target dynamics and the outputs are the correct weight values of the corresponding target dynamics. Such weights are set to the predictor module in (4) to guide the RLS algorithm to final values improving the converging speed. When the new values are ready from the network, it is necessary to wait for another cycle to verify the correctness of this prediction. If the retinal slip given by RLS is greater than the neural network one, the neural network output is used to predict the target velocity. In the other case, the RLS goes on learning the target dynamics, hence it is necessary to train the neural network on the new data.

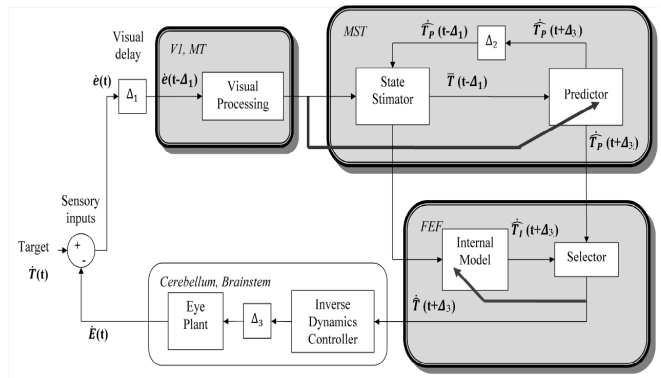

Figure 1 The model of a predictive smooth pursuit with prediction and learning of the target dynamics. The total time delay is: $\Delta_2 = \Delta_1 + \Delta_3$. The point means the velocity value, the bar means the estimate value and the hat means the predicted value

III. OBJECT TRACKER WITH OCCLUSIONS DETECTION

To emulate the gazing behaviour of humans in an experiment when the object of interest undergoes total occlusions, we use a method for object detection and tracking with built-in occlusion detection. Two properties of the tracking system are important for this work: it must be able to detect transitions between the states of full visibility and occlusions of the tracked object and it must be able to initialize autonomously the tracker when the object of interest reappears after an occlusion. The detection of the aforementioned transitions is important for our purposes because it corresponds to the events when humans toggle their eye movement behaviour from smooth pursuit to saccadic. We use the tracking system described in [26], exploiting the behaviour of the likelihood values it computes when the object of interest is partially occluded.

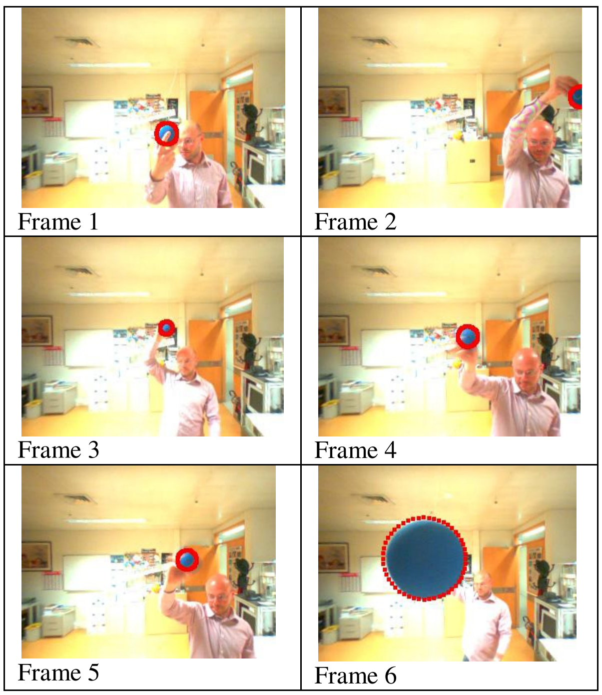

Figure 2: Performance of the particle filter tracker with moderate occlusion (frame 1 – notice the finger of the human user), severe occlusion (frame 2 – half the target is non visible due to image boundary), motion blur (frames 3 and 4) and large scale changes (frames 5 and 6)

The tracking system we use is based on Particle Filtering methods and exploits knowledge on the shape, color and dynamics of the tracked object. Each particle in the filter represents a hypothetical state for the object, composed of 3D position and velocity. Particles are weighted according to a likelihood function. To compute the likelihood of one particle we first place the points of the shape model around the 3D position encoded in the particle, with respect to the camera. Then we project these points onto the image plane obtaining two sets of 2D points. The sets of 2D points lie on the image on the inner and outer boundary of the silhouette that the tracked object would project if it were at the hypothetical position. The idea is that the color and luminance differences between the sides of the hypothetical silhouette are indicators of the likelihood of the corresponding pose. Object-to-model similarity positively influences the likelihood, while object-to-background similarity contributes to likelihood in the opposite direction.

When the object of interest is fully visible, the likelihood estimated by the filter as a whole is high. When the object gradually becomes occluded, the tracker continues working, but the estimated likelihood drops, only to rise again when the object reappears. The observation model we use enables us to detect occlusions and reappearance events just by setting a threshold on the likelihood value and by reinitializing the tracker, effectively running a detection process, each time the likelihood is below that threshold. The initialization is performed by generating a new particle set, sampling a predefined Gaussian distribution.

Figure 2 illustrates the performance of the tracker under moderate and severe occlusion, motion blur and drastic scale changes.

IV. ICUB HEAD PLATFORM

The RobotCub project has the twin goals of creating an open and freely-available humanoid platform, iCub, for research in embodied cognition, and advancing our understanding of cognitive systems by exploiting this platform in the study of cognitive development. To achieve this goal it has been planned to construct an embodied system able to learn: i) how to interact with the environment by complex manipulation and through gesture production & interpretation; and ii) how to develop its perceptual, motor and communication capabilities for the purpose of performing goal-directed manipulation tasks. The iCub robot has a physical size and shape similar to that of an about three year-old child, and will achieve its cognitive capabilities through artificial ontogenic co-development with its environment. The iCub has a total of 53 degrees of freedom organized as follows: 7 for each arm, 8 for each hand, 6 for the head, 3 for the torso/spine and 7 for each leg. In order to guarantee a good representation of the human movements, the iCub head contains a total of 6 DOFs: neck pan, tilt and swing and eye pan (independent) and tilt (common). The eyes cyclotorsion was ignored because it is not useful for control, and similar image rotations are easily produced by software. The elevation/depression from both eyes is always the same in humans, in spite of the existence of independent muscles. Similarly, a single actuator is used for the robot eyes elevation (tilt). Eye vergence is ensured by independent motors. Data regarding accelerations, velocities and joint range of the oculomotor system of human babies are not available, and very few studies exist in the literature of psychology or physiology. Overall, the iCub dimensions are those of about three-year old human child, and it is supposed to perform tasks similar to those performed by human children. First, it has been used the smallest range of saccadic speeds

as a reference and it has been used the ratio between neck/eye velocity (14% – 41%) and acceleration (2% – 4%) as an important design parameter. The eyes mechanism has three degrees of freedom. Both eyes can pan (independently) and tilt (simultaneously). The pan movement is driven by a belt system, with the motor behind the eye ball. The eyes (common) tilt movement is actuated by a belt system placed in the middle of the two eyes. Each belt system has a tension adjustment mechanism. For the necessary acceleration and speed, the iCub has Faulhaber DC micromotors, equipped with optical encoders and planetary gearheads. In order to guarantee easy assembly and maintenance procedures, the mechanical system architecture is also completely modular, in such a way that it is possible to remove and replace a certain module, without having to disassemble the entire structure. For vision, the main sensory modality, two DragonFly cameras with VGA resolution and 30 fps are integrated in the head. These cameras are very easy to integrate because the CCD sensor is mounted on a remote head, connected to the electronics with a flexible cable. In this way, the sensor head is mounted in the ocular globe, while the electronics are fixed to a non-moving part of the eye-system. All motor control boards are specially designed to fit in the size constraints of the robot. They are all integrated in the head and connect to the remote computer with a CAN bus. To measure the head position (kinesthetic information), the motors have magnetic encoders, for calibration purposes and noting that the protection system drift in case of overload condition, absolute position sensors were applied to each neck joint.

V. MODEL OF SMOOTH PURSUIT WITH OCCLUSIONS

This work proposes the integration of different systems in order to obtain a human like behavior of a predictive smooth pursuit of a dynamic target, with saccadic shift of gaze in case of occlusions.. The purpose of this work is to investigate the applicability of the smooth pursuit model on humanoid robots in order to achieve a human-like predictive behavior that can adapt itself to changing of environment and to learn from the experience. This model is able to predict target trajectories that present a second order dynamics also in presence of temporary occlusion. It is possible to extend this model to cope with more complex target motions with nonlinear dynamics as suggested in [27].
Figure 3 shows the entire system model. The first module is the visual tracker that allows rapid recognition of the object and provides its position in eye coordinates to the next modules. If the object is visible the information about target is processed and the smooth pursuit is executed. The smooth pursuit system requires only measurements of the retinal slip (the target velocity on the retina) to estimate the next target velocity. This information is obtained from the difference of the target position in eye coordinates sent by the tracking module, with respect to the sampling time of the cameras. When the system learns to predict the target dynamics the regression vector values reach convergence and the internal model stores these values. If the object disappears behind the occluder the tracking module stops sending data and another module starts to detect the edges in the image to find where the object will reappear. At this point the saccade generator module repeats the prediction of the target dynamic by a reiteration of (4) with the complete regression matrix, as follows:

$$\mathbf{Y}(\mathrm{t}+1) = \begin{bmatrix} 1 & \Delta\mathrm{t} \\ w1 & w2 \end{bmatrix} \mathbf{Y}(\mathrm{t}) \qquad (7)$$

Where Δt is the sampling time of the cameras and $\mathbf{Y}(\mathrm{t})$ represents the velocity and the position of the target. In order to obtain a long term prediction, the current state $\mathbf{Y}(\mathrm{t})$ has to be set equal to the previous iteration of (7). The (7) is repeated until the predicted position is equal to the edge detected from the previous module.

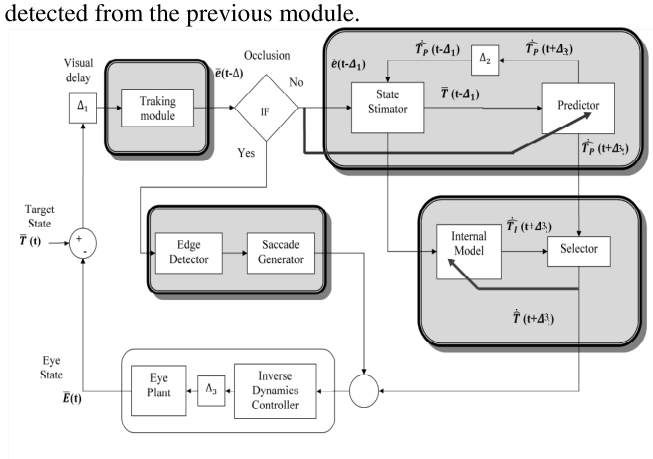

Figure 3 Model description of the tracking of an occluded object with prediction of the target dynamic

In this way it is possible to obtain the position and the velocity of the target reappearance. The robot switches gaze saccadicly across the occluder to continue tracking and arrives at the opposite side of the occluder slightly before the object.
In figure 4 are shown the results obtained from a simulation of this model on MATLAB Simulink for a sinusoidal dynamics with angular frequency of 1 rad/sec and amplitude of 20 rad. The occlusion range was chosen between -10 rad and 10 rad. In figure 4 are shown the eye position and the target position. When the target goes behind the occluder, the eye rapidly reaches the exact reappearance point predicted. In figure 5 the eye velocity has a peak on correspondence with the saccadic movement, then it goes to zero until target reappearance. The velocity of the saccadic movement reaches 300 rad/sec.

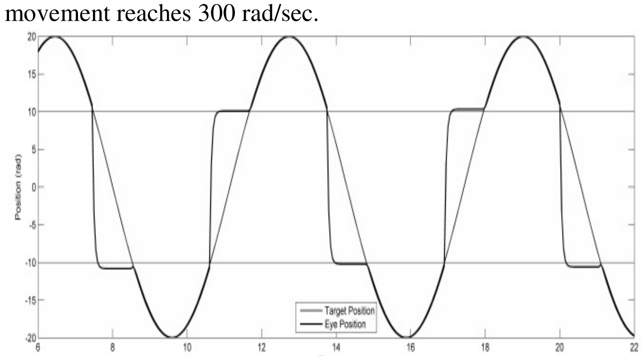

Figure 4 shows the simulation results of the eye position and the target position for a smooth pursuit tracking with occlusion of a sinusoidal target dynamics with angular frequency of 1 rad/sec and amplitude of 20 rad

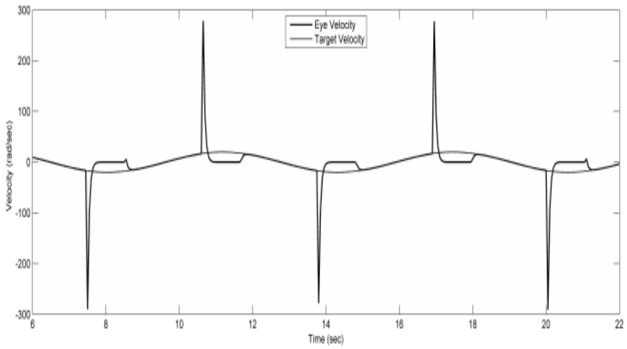

Figure 5 shows the simulation results for the eye velocity and target velocity

VI. RESULTS

Beyond the simulations we have performed results on the real robotic platform iCub (see Fig. 6).

Figure 6 – The iCub robot detecting, tracking and reaching for a known object.

The results are illustrated in Fig. 7 and on accompanying video (http://www-arts.sssup.it/tiki/tiki-download_file.php?fileId=42). A known target (a blue ball) is suspended from the ceiling with a string (snapshot 1). Once it is put into periodic oscillation, the robot starts estimating and tracking the ball trajectory (snapshots 2 and 3). It uses the predicted velocity to command the eye motions. Suddenly (snapshot 4),an occluder is put close to the ball. At moderate amounts of occlusions (snapshots 5 and 6), the robot still detects the ball and keeps tracking it. When the occlusion is almost complete (snapshots 7 and 8), the smooth pursuit tracking stops and the robot estimates when and where the ball will reappear, preparing a saccade. The saccade happens at the onset of reappearance (snapshots 9, 10, 11 – notice the large motion blur) and, at snapshot 12, the eyes are already centered at the target and ready to keep tracking it.

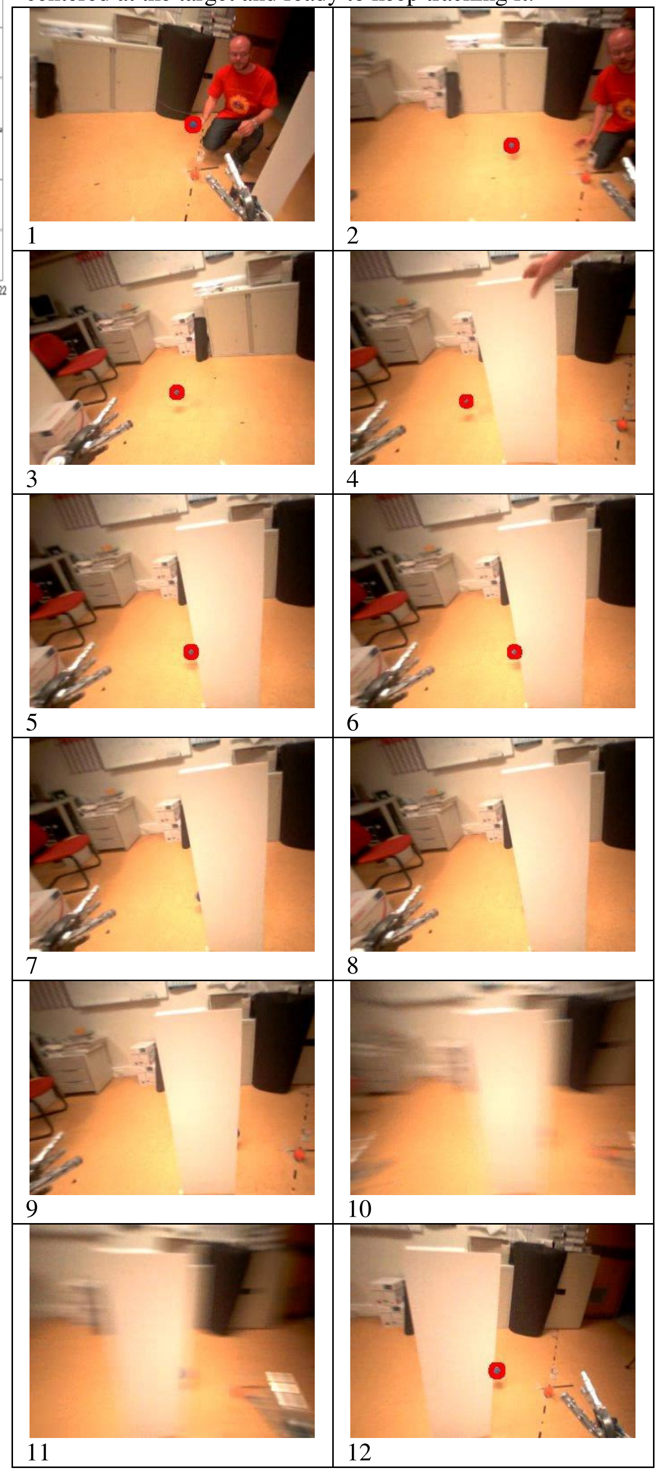

Figure 7 – Twelve frames of a tracking sequence illustrating the robot tracking across occlusions behavior. See explanation in the main text

During the robotic test phase, due to jitter and irregular behavior in the network communications between the track module and the smooth pursuit/saccade module, the RLS algorithm did not converge as well as expected. In the accompanying video one can observe that the tracking across occlusion behavior is functional but has some irregularities. The internal model is not very accurate due to noisy training data. This practical problem will be solved in a short term.

CONCLUSIONS

This work presents a model and a robotic implementation to address the problem of tracking targets across occlusions with predictive behavior, like in humans. The tracking is based on an integration model of smooth pursuit and saccades. Smooth pursuit is able to predict velocity of target dynamics. When the target is occluded the smooth pursuit movement is stopped and a saccade movement is commanded to the predicted reappearance of the target so that the gaze arrives at the opposite side of the occluder slightly before the target. Smooth pursuit is restarted when the target reappears. The model has been tested on MATLAB Simulink for sinusoidal dynamics with central occlusion and it has been implemented on iCub robot with the same settings and using a methodology based on 3D particle filter to track the target. This methodology is used to detect transitions between the states of full visibility and occlusions and it minimizes the noise during tracking of moving objects. In the long term we aim at extending the types of motions the robot is able to estimate and predict.

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