Hide and Seek
An Active Binocular Object Tracking System

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Abstract: We introduce a novel active stereo vison-based object tracking system for a humanoid robot. The system tracks a moving object that is dynamically changing its appearance and scale. The system features an inbuilt learning process that simultaneously learns short term models for the object and potential distractors. These models evolve over time, rectifying the inaccuracies of the tracking in a cluttered scene and allowing the system to identify unusual events such as sudden displacement, hiding behind or being masked by an occluder, and sudden disappearance from the scene. The system deals with these through different response modes such as active search when the object is lost, intentional waiting for reappearance when the object is hidden, and reinitialization of the track when the object is suddenly displaced by the user. We demonstrate our system on the iCub robot in an indoor environment and evaluate its performance. Our experiments show a performance enhancement for long occlusions through the learning of distractor models.

1 INTRODUCTION

Tracking objects in cluttered dynamic environments remains a major challenge. In fact, it can be argued that tracking problems can be made arbitrarily difficult if objects move erratically, are occluded for long stretches of time and can have a changed appearance when they return into view. In such cases even human observers will have difficulties identifying the correct target, see, e.g., (Triesch et al., 2002). In such difficult situations it is important to maintain and adapt models for the object's appearance and potential distractors and to explicitly detect problematic situations and respond to them in an intelligent way.

Here we present the Hide and Seek system (Fig. 1), which is an active tracking system implemented on a humanoid robot that utilizes stereo vision and segmentation and learns appearance models of objects and potential distractors. It uses these models to explicitly represent difficult situations such as occlusions resulting from the object hiding behind an occluder or being masked by it, sudden disappearance or displacement of the object, or other distractions and responds to them appropriately.

There is a significant amount of work on object tracking pertaining to tasks such as video surveillance, vehicle navigation, video editing, human-computer interaction, etc. However, most methods consider only prerecorded video streams or a passive/static camera. There are comparitively few attempts of tracking on a robotic platform which is especially challenging as the system should perform in real time using active cameras while the object as well as the robot move in a dynamic environment (for example, Falotico and Laschi 2009; Ginhoux and Gutmann 2001).

Figure 1: Hide and Seek running on the iCub robot.

In this work we develop an active tracking system that primarily involves frame-to-frame matching modulated by a segmentation scheme. We develop a feature based approach that has proven to be robust to occlusions and local deformations (for example, Ta et al. 2009). Their discriminative ability is also suitable for better object recognition. However, in the tracking scenario, they are sensitive to drastic changes in appearance and pose of the moving object thus los-

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ing global information of the tracked object over time. Feature extraction is also computationally expensive which would make the algorithm slow. To deal with this, our system utilizes a single class of image features that are used for a number of different objectives including stereo matching, frame-to-frame matching, and object and distractor modeling. To achieve real time performance we use GPU acceleration for feature processing [1].

Learning is an important part of our system that makes it more reliable and versatile. It has been shown that recognition and model based methods provide higher resistance to discontinuities and irregularities of the track (for example, Nelson and Green 2002). A hybrid model of frame to frame tracking along with object learning has also been demonstrated on a passive monocular camera (Kalal et al., 2012). In contrast to these, we learn models for both object and distractors in the scene for an active stereo vision scenario that not only rectifies tracker inaccuracies but also identifies unusual events and takes necessary action.

In the following, we will describe the architecture of our system, explain the methods used for modeling object and distractors, and present experiments demonstrating the advantage of including adaptive object and distractor models.

2 SYSTEM ARCHITECTURE

The overall system architecture is shown in Fig. 2. Images from both cameras are fed to the central tracking module for processing. The central tracking module is influenced by inputs from the object and distractor learning models and vice versa. The output from these modules are fed to the decision and motor control module that decides the course of action and sends commands to the robot. The output of this module is also fed back to the tracking and learning modules where this information is used to update relevant parameters.

2.1 Tracking Module Overview

The principle behind our system is to combine efficiently the temporal and spatial information of the moving object at every time frame. We use feature descriptors (local cue) that add resistance to perturbation and occlusions while stereo segmentation (global cue) updates object information by adding new features

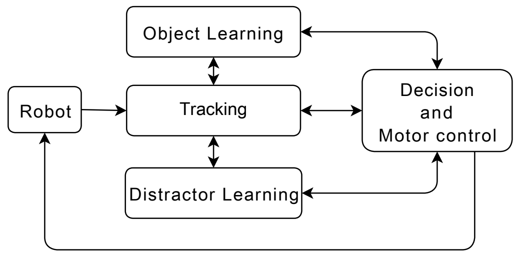


Figure 2: System Architecture.

that are revealed as the object is turning or changing its shape while moving. A block diagram of the tracking module is given in Fig. 3. It comprises feature extraction in left and right images, stereo matching, frame-to-frame matching, estimation of object center, bounding box, and segmentation. An internal memory aggregates necessary information over time. The estimated location of the object is fed to the decision and motor control. Inputs from various parts are fed to object and distractor learning modules (shown by dotted lines in Fig. 3).

2.2 Feature Extraction

We calculate local feature descriptors around identified interest points on the images. Interest points are detected using the FAST corner detection (Rosten and Drummond, 2006). We use Gabor wavelets as features, which have the shape of plane waves restricted by a Gaussian envelope function. At each interest point we extract a 40-dimensional feature vector (also referred to as a Gabor-jet or Gabor-descriptor) resulting from filtering the image with Gabor wavelets of 5 scales and 8 orientations, see (Wiskott et al., 1997) for details. These descriptors are highly discriminative and repeatable from frame to frame.

2.3 Stereo Matching and Segmentation

We find correspondences between features on left and right images by performing a brute-force search for best matches. The similarity between any two descriptors $\mathbf{d}^{(i)}$ and $\mathbf{d}^{(j)}$ is calculated as their normalised inner product and denoted $S(\mathbf{d}^{(i)}, \mathbf{d}^{(j)})$. Each feature on the left image is associated with the best matching feature on the right image if the similarity measure S between the two descriptors exceeds a preset threshold (0.9 in our case). The advantage of this brute force approach is that it does not require calibration of the moving cameras. Figure 4 shows an example of stereo matching. For better visibility, matching lines are shown for only few objects in the scene and the saturation of the line colors are made proportional to their corresponding stereo disparities.

[1]Speed of 20 fps is achieved on GPU which was observed to be 4-5 times faster than that on CPU.

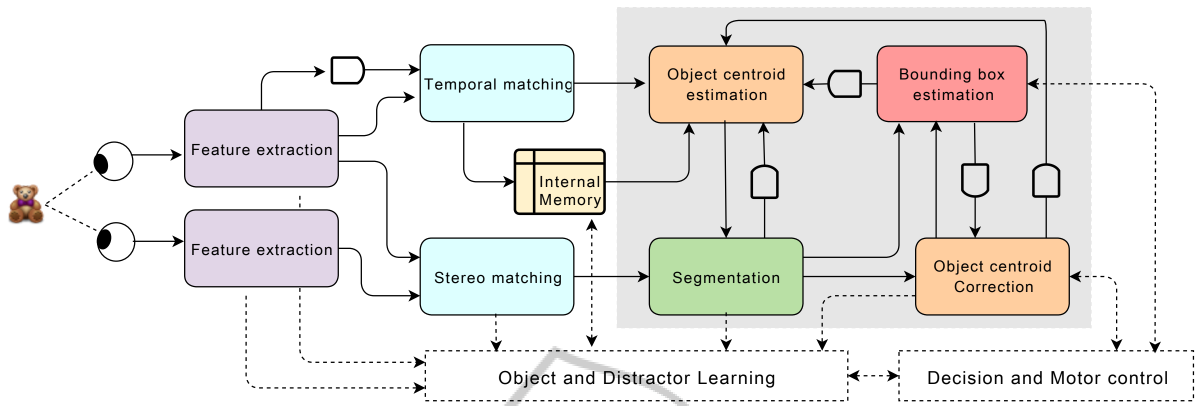


Figure 3: Block diagram of the tracking module. Rectangular boxes indicate processing units. Boxes with same color indicate identical processes operating on different inputs. The symbol resembling a cylinder indicates a time delay of 1 frame.

We use the information about matched features for also segmenting the objects in the scene. This is done by clustering the matched interest points from the primary camera (left in our case) into different groups. A greedy clustering scheme is used that starts with a single interest point and adds new ones if their x-position, y-position, and disparity are all within 5 pixels of any existing cluster member. Figure 5 illustrates an example wherein the objects in the scene have been clustered into different segments.

2.4 Temporal Matching

Tracking in an active vision system has to cope with image movement due to camera motion as well as object movement. Matching local descriptors from frame to frame is a robust approach in such a scenario.

An image at time t is represented by a feature set $\mathbf{F}_t$ consisting of N_t elements. Every feature element $\mathbf{f}_t$ is represented by a tuple containing its Gabor descriptor $\mathbf{d}_t$ and its location $\mathbf{x}_t$ on the image.

$$\mathbf{F}_t = \left\{\mathbf{f}_t^{(i)}\right\}_{i=1:N_t}, \ \mathbf{f}_t^{(i)} = \left[\mathbf{d}_t^{(i)}, \ \mathbf{x}_t^{(i)}\right], \text{ where } \mathbf{x} = (x,y). \quad (1)$$

We find best matches between frames $t-1$ and t by brute force exhaustive search and associate every feature in the previous frame $\mathbf{f}_{t-1}^{(i)}$ with a description $\mathbf{q}_{t-1}^{(i)}$ that contains the index m of the best matched feature in $\mathbf{F}_t$, the similarity s of this best match, the associated image flow vector $\Delta\mathbf{x}$, and a counter n indicating the number of times a given feature was tracked successfully in the past. As explained in the next section, the features with a high count n are given higher weights for estimating the object location. The cyan lines in Fig. 6 illustrate the matching process from time $t-1$ to t. The thinkness of the lines is proportional to the base 2 logarithm of the count n of the corresponding feature to indicate that relevant features are given higher weights. Black lines indicate wrong matches that have been filtered out as explained in the next section.

Figure 4: Example of stereo matching.

2.5 Track Estimation

In this section we explain how the system efficiently uses temporal and stereo matching information to estimate the object location at every frame. The part of the system responsible for this is shaded with gray in Fig. 3 and an example has been provided in Fig. 6 depicting outputs of different processing units (note the color correspondence between the respective parts).

During tracking we estimate the object's location as well as its bounding box at every frame. The bounding box of the object, which is a rectangle placed around its centroid, is calculated using the object segmentation information at the current frame. The width and height of the bounding box are obtained by finding the mean of absolute distances of

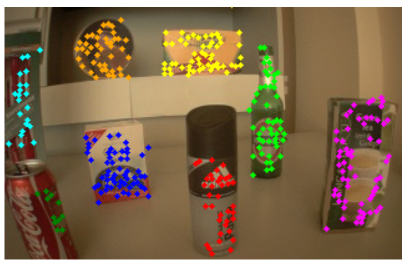


Figure 5: Example of segmentation based on feature proximity in the image plane and in depth.

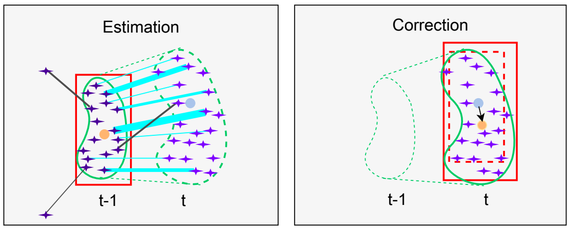


Figure 6: Illustration of an instance of tracking that is processed within the gray portion of the blockdiagram in Fig 3. Colors in this image match their corresponding processing units (boxes) in the blockdiagram.

the segmented feature points from the current object centroid. The size of the bounding box is averaged over a few frames which helps in rejecting bad segments caused by momentary occlusions.

In our system, bounding box and feature matching count provide global consistency and long term stability to the track. On the other hand, object segment and new features provide adaptibility by adding new information about the object.

Centroid Estimation. As illustrated in Fig. 6 an object changes its location, scale and appearance from time $t-1$ to t. We estimate the object centroid at time t using the matched features from time $t-1$ to t. We form a set U_{t-1} from the locations $\mathbf{x}_{t-1}^{(j)}$ in $\mathbf{F}_{t-1}$ that fall on the object (see purple dots in Fig. 6) such that

$$U_{t-1} = \left\{ \mathbf{x}_{t-1}^{(j)} \in \left(segment(\mathbf{F}_{t-1}) \bigcap BB(\mathbf{F}_{t-1}) \right) \right\}$$

where BB is the bounding box placed around the object centroid at $t-1$.
Using the matched information we find another set U_t in $\mathbf{F}_t$ such that

$$U_t = \left\{ \mathbf{x}_t^{(m(j))} : \mathbf{x}_{t-1}^{(j)} \in U_{t-1} \right\}$$

where $m(j)$ is the index of the matched feature at t for every j at $t-1$.
We now calculate the weighted median of the matched feature locations in both x and y axis to obtain the initial estimate of the centroid of the object at time t.

$$\hat{\mathbf{c}} = Median\left[\mathbf{x}_t^{(m(1))} \diamond \log\left(n_{t-1}^{(1)}\right), \ldots, \mathbf{x}_t^{(m(j))} \diamond \log\left(n_{t-1}^{(j)}\right) \right]$$

where $\diamond$ indicates that left hand factor is weighed by the count equal to right hand factor. The parameters m and n are as described in section 2.4.

The estimated centroid of the object may not be its true centroid at time t since the current segment of the object may contain new features due to object rotation or change in shape (if the object is not rigid). In order to compensate for this, we first pick the right segment of the object, $segment(\mathbf{F}_t)$, at time t by choosing a segment from the scene on which the estimated centroid falls. We then estimate the true centroid of the object as follows:

$$\mathbf{c} = Median\left[\mathbf{x}_t^{(1)}, \mathbf{x}_t^{(2)}, \ldots, \mathbf{x}_t^{(i)} \right]$$
$$\forall \mathbf{x}_t^{(i)} \in [segment(\mathbf{F}_t) \bigcap BB(\mathbf{F}_t)]$$

where $BB(\mathbf{F}_t)$ is placed around $\hat{\mathbf{c}}$

The calculations above are done only for the primary camera. The location corresponding to $\mathbf{c}$ on the other camera is obtained by using the stereo matching information (see section 2.3). The resultant stereo location is sent to the decision and motor control module [2].

3 LEARNING SYSTEM

As tracking proceeds the system learns models for both the object as well as potential distractors. The object model helps in the case of swift movements and occlusions. The distractor model helps to build a clean model for the object, to avoid distraction of the track by other objects and to identify unusual events.

3.1 Object Learning

Tracking is susceptible to occlusions as well as changes in object appearance. In order to help the system track an object for long durations we learn an object model (see also Chandrashekhariah et al. 2013) using the same feature descriptors and the same processing blocks that are used for the tracking scheme.

The object model should capture the stable appearance of the object rather than picking up irregularities that would arise due to object occlusions. This demands carefully choosing features that are stable. We mark a feature on the object as eligible for entering the object model only when it has been tracked successfully for a certain time i.e. $n > \gamma$. All those features that enter the object model will eventually form a feature dictionary for the object.

Dictionary for Object Modeling. The feature dictionary is a buffer that has a fixed amount of memory as shown in Fig. 7. The dictionary is initially empty when the tracking begins. Every new feature that enters the dictionary will enter its descriptor vector $\mathbf{d}$, location (x,y) relative to the object center and counter k (initialized to 1). If the dictionary already

[2]The motor control part uses the iKinGazeCtrl module of the iCub to control the neck and eye coordination while tracking (Pattacini, 2010)

	Object Dictionary			
	Descriptor	X	Y	Count
1	d1	x1	y1	k1
2	d2	x2	y2	k2
⋮				
N	dN	xN	yN	kN

Figure 7: Object dictionary.

contains a similar feature, then the associated count k in the dictionary is incremented. A new feature that enters the dictionary after it gets full will flush out the element that has the smallest value of k if it does not match with any of the existing features and its location (x,y). Eventually the developed dictionary represents a model for the object. Having a dictionary of limited size helps in continuously evolving the model with the recent variations of the object appearance. It also gives room for correcting the model in case the tracking inaccuracies have incorporated wrong features into the model.

Recognition. The recognition module is always running in the background to identify if the object has been displaced while tracking. It uses the saved features in the dictionary to ascertain the presence of the tracked object in the scene. Each feature in the dictionary is matched with all the features on the incoming image to see if there is a valid match that exceeds the preset similarity threshold (0.9 in our case) and declare it as eligible for casting a vote. These eligible features vote for the centroid location (using the (x,y) information from the dictionary) with respect to the location of the feature it matches on the image (see Fig. 8). These votes are collected in a 2D space (a matrix of image size) are smoothed using a box filter or a gaussian filter and the global maximum is found. The object is declared to be present in the scene if this location contains a count higher than a suitable threshold (10% of dictionary size in our case where the dictionary contains 300 feature elements).

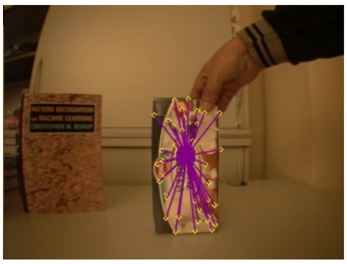


Figure 8: Object recognition.

3.2 Distractor Learning

In this work, we also develop a model for other objects in the scene considering the fact that they can distract the tracking process and hence should be identified. We learn short term models for only potential distractors in the scene that would affect the tracking process in the near future.

A dictionary for the distractor model is structured in the same way as for the object dictionary but without having the location information (x,y) of features. This is because the contents of the scene as well as their locations change continuously in an active vision scenario making it futile to save feature locations. It is also a challenge to selectively pick critical parts of the scene for learning (using a dictionary of finite size). We hence pick only those objects or parts of the scene for learning that are likely to occlude the object shortly.

Let $\mathbf{c}_L$ and $\mathbf{x}_L^i$ be object centroid and feature location respectively (on the left camera). The vector $\mathbf{c}_L - \mathbf{x}_L^i$ indicates the distance vector from the feature to the object centroid whose euclidean distance $D_i = \|\mathbf{c}_L - \mathbf{x}_L^i\|$. Let $\Delta\mathbf{c}_L$ and $\Delta\mathbf{x}_L^i$ be object and feature flow vectors respectively. The relative flow vector of a feature with respect to the object will then be $\Delta\mathbf{x}_L^i - \Delta\mathbf{c}_L$ which indicates motion in one time frame. We calculate the distance component of the relative feature flow vector along the direction of distance vector which is given by :

$$\Delta D_i = \frac{\langle \Delta\,\mathbf{x}_L^i - \Delta\,\mathbf{c}_L\ ,\ \mathbf{c}_L - \ \mathbf{x}_L^i \rangle}{\|\mathbf{c}_L - \ \mathbf{x}_L^i\|}\ .$$

The sign of the term ΔD_i indicates the direction of motion of the feature. The time taken by a given feature at $\mathbf{x}_L^i$ to reach the object centroid in the image plane is given by :

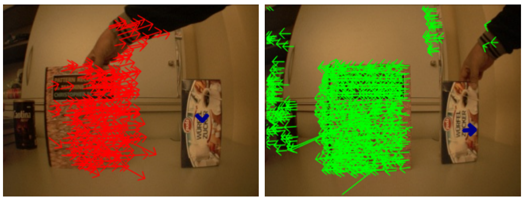
$$\tau = \frac{D_i}{|\Delta D_i| \times fps}\ ,$$

where fps is the speed of the algorithm in frames per second.

The features that are going to occlude the object in less than 5 seconds are considered critical and updated to the distractor model (see Fig. 9a). However, features of the objects that are moving away from the object (when ΔD_i is negative) are not considered harmful for tracking and hence they are neglected (see Fig. 9b).

Distractors in the scene that are behind the object by a considerable depth are neglected, i.e. the following disparity condition should be satisfied for a positive value of δ.

$$(\mathbf{c}_L(x) - \mathbf{c}_R(x)) - \left(\mathbf{x}_L^i(x) - \mathbf{x}_R^i(x)\right) > \delta \quad \forall i$$



(a) (b)

Figure 9: Distractor model update example : (a) Features that are included in the model. (b) Features that are not included in the model.

However, distractors in the front are considered a threat irrespective of their position between the camera and the object.
In addition, self occlusion of the object is also neglected by not considering the features belonging to the object (i.e. $\in segment(\mathbf{F}_t)$)

Distractor Recognition. A Distractor in the scene is recognized using the distractor dictionary in the same manner as that of object recognition. However, the features will vote for their absolute locations rather than for the centroid. The presence and location of the distractor is decided by merely calculating the density of the distractor's features that are overlapping/masking the tracked object (see Fig. 10).

Figure 10: Distractor recognition.

4 SYSTEM STATES

The system goes into different states as shown in Fig. 11 depending on inputs received from tracker and recognition (object and distraction). This will further guide the decision module of the architecture (Fig. 2).

The system primarily contains four states, each of which changes to the other based on events. An event is a logical combination of outputs of different parts of the system namely - tracking, object recognition and distractor recognition (see Table 1). Each of these parts is associated with two quantities - output status (true/false) and output location.

1. **Initialize.** The system is initialized with an object that is in the center and close to the stereo cameras. When an object is brought in the region of focus the system triggers and starts tracking it.

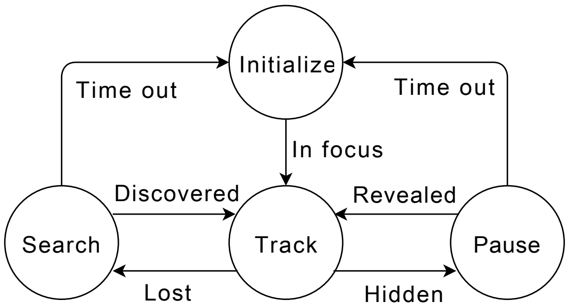


Figure 11: States of the system.

2. **Track.** This is the normal state of the system unless the object is lost or hidden. When the user displaces the object to a different location in the scene with swift movements the object recognition helps in restoring the track.
3. **Pause.** The system goes to a pause mode when the object is masked by a moving occluder or the object moves behind an occluder. This is known when the tracker location overlaps with a patch $\mathbf{P}$ that is identified as an occluder by the distractor model i.e. when $(\mathbf{c} \in \mathbf{P})$, concurrently there is no output from the object recognition $(R = 0)$. The tracking resumes when the object is revealed again $(R = 1)$.
4. **Search.** System starts searching when the object is lost i.e. when the user moves it out of the scene. When an object suddenly disappears or when a distractor suddenly masks the object, the focus of the cameras in depth shifts drastically from on object to either behind or front, again followed by no output from the object recognition within the scene purview, i.e. when $T = 0$ and $R = 0$. A random search is then initiated in the direction in which the object was lost until it is discovered using recognition output. All the model updates are stopped in this state as well as the pause state.

5 SYSTEM EVALUATION

Performance evaluation of object tracking often requires ground truth information of the object as in the case of prerecorded images/videos (Yin et al., 2007). However, this information is not easily available in a realtime active vision system. There are other algorithms in the literature that use no ground truth information but spatial and temporal differences of object cues with respect to its surrounding as an alternative.

Table 1: System states and events.

System	**Output**
Tracker	Status T(1/0), Centroid **c**
Object Model	Recognition R(1/0), Location **l**
Distractor Model	Occluded O(1/0), Patch **P**
Events	**Combination**
In focus	Object is in center and close
Displaced	$R=1 \wedge \|\mathbf{l}-\mathbf{c}\| > Threshold$
Masked/Hidden	$O=1 \wedge R=0 \wedge \mathbf{c} \in \mathbf{P}$
Revealed	$O=1 \wedge R=1$
Lost	$T=0 \wedge R=0$
Discovered	$T=0 \wedge R=1$

This is again used only in the case of self occlusions but not for occlusions from other objects in the scene (Erdem et al., 2004). In order to keep the evaluation procedure simple for unusual active binocular tracking setting we are using, we evaluate our system in a staged manner by comparing performance of the partial system with the full system in different scenarios.

5.1 Experimental Setup

We conduct our experiment on the iCub robot head in a regular office room with cluttered background (see Fig. 12). We collect various objects such as a coffee cup, tea packet, coke tin, books etc that have sufficient texture on them. We ask a subject unfamiliar with the system to test the algorithm while we count the success and failure rates for various scenarios:

1. No Occlusion Scenario. In this case the object moves in front of a cluttered background making changes in the scale and in-plane/in-depth rotation of the object. The algorithm is mainly tested for three cases:
   - Displacement. Swift and erratic movements of the tracked object.
   - Distraction. Bringing another object next to the object in focus and push it or move them together
   - Merging: Moving the object far away from the robot and merging it with the background for a significant amount of time.
2. Severe Occlusion Scenario. In this case the object is completely occluded by other objects. The object is either occluded by another object (masking) or the object goes behind an occluder (hiding). We further consider two scenarios:
   - Momentary Occlusions. We occlude the object for a short time of the order of 2 to 5 seconds.
   - Long-term Occlusions. We occlude the object for a long time of the order of 10 to 30 seconds.

Figure 12: An instant of the experiment wherein an object is hiding behind an occluder.

3. Object disappearance scenario: In this case the object is suddenly moved out of the scene to see if the system can search and discover the lost object.

5.2 Performance Quantification

We conducted two day long experiment (comprising 345 trials in all) and performance was quantified for various scenarios.

No Occlusion. We initially compare a partial system having no learning modules with the full version of the system, for the no occlusion scenario. Since there are no complete occlusions the distractor model would not add much improvement to the performance and hence it is ignored. We ask the subject to randomly select 3 objects and make 5 trials for each of the above cases (90 trials in all). We count the number of trials in which tracking was successful throughout the sequence. The percentage of success is listed in Table 3. We observe that the performance of the system improves by incorporating learning that rectifies inaccuracies of the tracker. It particularly helps in the case of merging. Since in our system the object segment evolves over time, the system would gradually fail when the object is merged with the background for significant amount of time. This can be avoided to a good extent by introducing learning.

Occlusion. We then test the system in the occlusion scenarios wherein we compare the system containing object learning alone with the full system also containing the distractor model. We ignore the partial system without learning in this case since it is bound to fail in case of complete occlusions. Table 3 lists the performance in terms of Precision that is calculated as $TP/(TP+FP)$ where TP and FP are true and false positives respectively. FP originates if the system mistakes the occluder for the object. The numbers listed in the table are averaged over 30 trials (5 for each of 6 objects with different occluders; 240 trials in all).
We observe that the precision gets better with the disctractor model since it helps the system to stop

Table 2: Performance evaluation : No occlusion scenario.

	No learning	**Full system**
Displacement	53%	73%
Distraction	86%	93%
Merging	0%	80%

Table 3: Performance evaluation : Occlusion scenario.

	No distractor learning		**Full system**	
Occlusions	Mask	Hide	Mask	Hide
Momentary	90%	66%	100%	96%
Long-term	63%	60%	90%	73%

updating the object model when it is occluded. This is even more evident in the case of long-term occlusions. We also observe that the performance for masking is better than hiding because of object perspective change, camera jitter etc. Any mistake in the distractor identification would harm the system more in the case of long term occlusions.

Searching. In the end, we also test the searching performance when the object is lost. We count how many times the object was discovered in less than 30 seconds. We observed that the searching was successful in 73% of the trials (15 in all).

The tracker performance recorded as a video can be viewed at https://fias.uni-frankfurt.de/neuro/triesch/videos/icub/tracking/.

6 CONCLUSIONS

We developed and demonstrated an active stereo-vision based tracking system on the robot. In contrast to other systems in the literature, our system attempts to identify unusual events in the scene and take necessary actions. The system is also generic enough to be applied for applications such as face/pedestrian tracking on static/active cameras (an instance of face tracking is shown in Fig. 13). There is a scope for further improvement in every part of our system. However, the present system clearly demonstrates how object and distractor models allow to recognize difficult tracking situations and to respond to them appropriately. This brings us one step closer to building tracking systems with human level performance.

Figure 13: An instant of face tracking.

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