Active Object Tracking using Context Estimation: Handling Occlusions and Detecting Missing Targets

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Abstract When performing visual servoing or object tracking tasks, active sensor planning is essential to keep targets in sight or to relocate them when missing. In particular, when dealing with a known target missing from the sensor’s field of view, we propose using prior knowledge related to contextual information to estimate its possible location. To this end, this study proposes a Dynamic Bayesian Network that uses contextual information to effectively search for targets. Monte Carlo particle filtering is employed to approximate the posterior probability of the target’s state, from which uncertainty is defined. We define the robot’s utility function via information theoretic formalism as seeking the optimal action which reduces uncertainty of a task, prompting robot agents to investigate the location where the target most likely might exist. Using a context state model, we design the agent’s high-level decision framework using a Partially-Observable Markov Decision Process. Based on the estimated belief state of the context via sequential observations, the robot’s navigation actions are determined to conduct exploratory and detection tasks. By using this multimodal context model, our agent can effectively handle basic dynamic events, such as obstruction of targets or their absence from the field of view. We implement and demonstrate these capabilities on a mobile robot in real-time.

Keywords Active perception · Context estimation · Object tracking · POMDP

1 Introduction

This paper addresses visual-based active object tracking using mobile sensor platforms. Recently, low cost vision sensors and object detection algorithms have been broadly available (Redmon et al., 2016), upping the development of new object tracking capabilities. Visual information of objects can easily incorporate semantic information of known targets to resolve ambiguity related to data association in cluttered environments (Makris et al., 2011). However, vision-based object tracking suffers from occlusion from overlapping objects, or missing targets from the field of view (FOV) (Xiang et al., 2015; Yun et al., 2017). To overcome these difficulties, many researchers have investigated “active” approaches to change or move camera states in order to keep tracking targets in sight. In other words, the focus of previous research has shifted from passive to active perception (sensing) to handle more dynamic tasks such as pick/place, and dynamic target grasping (Kaelbling and Lozano-Pérez, 2012; Eidenberger et al., 2009b; Arora and Papachristos, 2020). However, there is little work to solve the more challenging situations involving long-term occlusions or losing sight of targets unexpectedly. Recently, deep reinforcement learning methods have been applied for active object tracking (Luo et al., 2019) and visual-servoing tasks (Shi et al., 2018) showing target recovery capabilities, but these methods are limited to simulation environments or do not perform active search when facing occlusions like we do in our work.

The authors of (Bajcsy, 1988) firstly described active perception as “a problem of controlling strategies applied to the data acquisition process which depends on the current state of the data interpretation and the task of the process”. Similarly, this paper proposes an active perception framework that seeks optimal control inputs that reduce target uncertainty.
based on information theoretic costs (Eidenberger et al., 2009a). Information theoretic approaches have been widely used in state-estimation and control of mobile sensor systems such as mapping (Chorrow et al., 2015; Julian et al., 2014), Simultaneous localization and mapping (SLAM) (Valencia and Andrade-Cetto, 2014), or object pose estimation (Wu et al., 2015). Related to our work, (Ryan and Hedrick, 2010) uses Bayesian estimation and information theoretic cost to reduce uncertainty of target locations.

Object tracking with Bayesian estimation lacks support for dealing with the absence of targets since direct measurements might not be available. In such situations, we convert the tracking problem into an object search problem. Object search can be solved by finding the most informative actions to re-locate lost targets. Since there is no direct observation of an object, we aim to obtain an optimal action policy based on the probabilistic belief of possible target locations. (Bourgault et al., 2003) investigated optimal search strategies to minimize the expected time to find lost targets within probabilistic frameworks. Other probabilistic formulations for object search have been considered such as (Bertuccelli and How, 2006; Lau et al., 2006; Chung and Burdick, 2012). Most of these methods reduce the search space using a discrete-grid world or graphical structure, since computing the optimal search actions with uncertainty is known to be an NP-hard problem (Tseng and Mettler, 2017). Reformulating optimal search by reducing the search space mitigates the computational burden. However, these methods do not deal with dynamic situations such as occlusions or missing targets. Other works have shown progress recovering missing targets such as (Radmard and Croft, 2017) or (Radmard et al., 2018). However, since these studies do not utilize semantic information of objects and only handle occlusions using geometric information, there are less versatile than our method; for instance they cannot reason whether an object is occluded or has suddenly disappeared. In addition, although an occlusion-aware planning strategy for multiple robots has been studied using an information theoretic approach (Hausman et al., 2016), this work has the critical assumption that tracking never fails completely because of occlusions. Recently, Shi et al. (Shi et al., 2018) applied reinforcement learning to resolve occlusions during image-based visual servoing tasks, focusing on finding missing features from QR code images without using semantic information or context. Once again, such method provides less versatility to complex situations than our method.

Inferring the possible location of targets draws inspiration from human perceptual capabilities (Aydemir et al., 2013). Our research proposes estimating possible target locations based on predicted context information. By using prior knowledge of the target’s surrounding or past experience of the sensing process, the quality of a target’s prediction can be improved significantly. From this perspective, providing high-level information (domain knowledge or context) to a state estimator is strongly desirable (Denzler and Brown, 2002; Kaelbling and Lozano-Pérez, 2013). The main challenge with this concept is that this estimation framework needs to be formulated so that it can be used simultaneously to address tracking, searching of objects, and recovering from occlusions. To resolve this difficulty, our study proposes to utilize domain knowledge for target estimation using probabilistic tools such as Dynamic Bayesian Networks (DBN), particle filters, and POMDP.

We estimate context states using probabilistic beliefs. Computing an optimal action over the belief space can be formulated as a Partially-Observable Markov Decision Process (POMDP). There exist approximate solutions for low dimensional systems (Porta et al., 2006) and locally optimal solutions for continuous state and action spaces (Van Den Berg et al., 2012; Bai et al., 2014). Furthermore, online POMDP solvers for quite large dimensions are studied (Silver and Veness, 2010; Ye et al., 2017). Similarly to (Sridharan et al., 2013; Li et al., 2016), we utilize POMDP to high-level planning in order to achieve real-time performance with an online solver.

By estimating their context, our robots can take optimal decisions based on increasing the information gain. For example, when a target object is present, our robot will attempt to keep targets in its FOV by controlling its head or mobile base. When an occlusion occurs, our robot will move to the optimal sensor configuration obtained by solving the alluded information theoretical control problem. In addition, when targets suddenly disappear, our robot will search for them based on context information. For our study, we assume that objects can not move by themselves but only by nearby people. With this assumption, our robot’s logical action is to find targets near observed people. When no person is present, our robot will start exploring the area around it to locate people.

In summary, the main contributions of this work are 1) devising a probabilistic framework for leveraging context, which adds a situational layer of information for more versatile active object tracking (see Fig. 4 for an example of situational context states) such as resolving occlusions
and missing, 2) building a bridge between particle filtering and POMDP enables achieving not only high-level decision-making but also constructing a sampling-based optimization problem to find the optimal sensor configuration using the information theoretic approach. Lastly, 3) integrating a realistic demonstration with a mobile robot for validating the newly defined capabilities.

2 State Estimation

2.1 Bayesian Filtering: Active Object Tracking

Bayesian filtering is a great tool to estimate the state of dynamic systems recursively in a probabilistic manner. This approach attempts to construct the posterior probability of a state based on a sequence of observations. In general, an active object tracking problem (object tracking with active sensing) can be formulated with a set of models: motion transition model \( p(x_k|x_{k-1}) \), sensor (robot) motion model \( p(q_k|q_{k-1}, u_{k-1}) \), and measurement model \( p(z_k|x_k, q_k) \), where \( x_k \in \mathbb{R}^3 \), \( q_k \), \( u_k \), and \( z_k \) are target states, sensor (robot) states, control inputs, and observations at time step \( k \), respectively. In this study, a target state is described as the 3D position of an object, and \( q_k \) denotes the robot’s base and its camera’s configuration, namely, \( q_k = (x, y, \theta, q_{tilt}, q_{pan}) \). Here, a sensor motion model is the probabilistic form of the robot’s forward dynamics, which assumes that \( q_{k+1} \) is observable. In addition, \( z_k \) is the detection output through an object recognition algorithm and point cloud processing, encoding the 3D position of the observed targets.

The goal of filtering is to estimate the target state \( x \) at time \( k \), namely, the posterior distribution, using the a priori estimate (prediction step) and the current measurement of the sensor (update step). Assuming that the prior probability \( p(x_{k-1}|z_{1:k-1}) \) is available, given sensor configuration \( q_k \) at time \( k \), the estimated state can be updated as

\[
p(x_k|z_{1:k}) = \frac{p(z_k|x_k, q_k)p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1}, q_k)} \tag{2}
\]

where \( p(z_k|z_{1:k-1}, q_k) = \int p(z_k|x_k, q_k)p(x_k|z_{k-1})dx_k \). For the update step, the measurement \( z_k \) is used to modify the prior estimate, leading to obtaining the posterior distribution of the current state. Finally, after calculating the target’s belief state \( p(x_k|z_k) \), the goal of active sensing is to provide optimal sensor control inputs to track the target or to find it if its lost.

2.2 Context Modeling

In general, for object tracking, a transition model is assumed to be known based on a constant velocity model hypothesis with white noise, i.e. \( P(x_k|x_{k-1}) = x_{k-1} + v_{k-1} \Delta t + \nu \) where \( \nu \) represents white noise. However, this approach is inefficient in active object tracking since targets might be frequently missing, meaning that \( v_k \) is unavailable. Thus, inspired by how humans seem to track objects, it would be beneficial to understand the current situational context in order to effectively estimate possible locations of lost targets. To leverage this abstract knowledge or context, we employ a Dynamic Bayesian Network model to infer the possible state of targets. Consequently, when an agent begins looking for a missing target it will benefit by knowing the belief state of the context and trying to find it based on such information.

2.2.1 Dynamic Bayesian Networks

DBN is an extension of Bayesian Networks, a graph model for representing causal relations and conditional dependencies, for temporal processes, which can evolve over time. The proposed model is shown in Fig. 2, where \( c_k \) denotes the context state at time step \( k \), and \( y_k \) is the observation of the context state. Since target states can depend on context states, this model can be directly applied to Bayesian filtering as a transition model for prediction. In other words, instead of using \( p(x_k|x_{k-1}) \), we propose to use \( p(x_k|c_{k-1}) \) as the motion model, i.e.

\[
p(x_k|z_{1:k-1}) \approx \int p(x_k|c_{k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1}. \tag{3}
\]

In this sense, target states can be predicted using context states, which in turn can be estimated using context transition models and context measurements.

2.2.2 Hybrid Motion Model

More precisely, the target transition model can be reformulated using context states as

\[
p(x_k|c_{k-1}) = \int p(x_k|c_k)p(c_k|c_{k-1})dc_k. \tag{4}
\]
where the weighted sum of all components, i.e., the probability density of the GMM is equivalent to
\[ q(x_k | z_{1:k}) = \sum \frac{p(x_{0:k} | z_{1:k})}{q(x_{0:k} | z_{1:k})}. \] (8)

Assuming the Markov property, the proposal density can be decomposed into the prior proposal density and the propagated density as
\[ q(x_k | z_{1:k}) = q(x_k | x_{k-1}, z_{1:k})q(x_{0:k-1} | z_{1:k-1}). \] (9)

Thus, this equality yields
\[ w_k' = w_{k-1} \frac{p(z_k | x_k')p(x_k' | x_{k-1})p(x_{0:k-1} | z_{1:k-1})}{q(x_k' | x_{k-1}, z_{1:k})q(x_{0:k-1} | z_{1:k-1})} \]
\[ = \frac{p(z_k | x_k')p(x_k' | x_{k-1})}{q(x_k' | x_{k-1}, z_{1:k})} w_{k-1} \] (10)

Here, a common choice for \( q(x_k' | x_{0:k-1}, z_{1:k}) \) is the motion model \( p(x_k' | x_{k-1}) \) which minimizes the variance of \( p(x_k | z) \). Also, as mentioned before, in the above equations we use Eq. (5) to estimate the process \( p(x_k' | x_{k-1}) \). Based on Bayesian filtering, at every time step \( k \), these weights can be recursively updated from the time step \( k - 1 \),
\[ w_k = w_k' \frac{p(z_k | x_k', q_k)}{\sum_{j=1}^{N} p(z_k | x_k', q_k)}. \] (12)

### 2.4 Sensor Model

The sensor model, \( p(z | x, q) \), has the form of a joint distribution for \( z, x \), and \( q \). This model must consider the case of an empty measurement set (i.e. when the target is missing). In addition, the sensor model depends on whether the target is within the FOV or not. The FOV can be formulated as a function of \( q, f(q) \), given the robot’s configuration (Freda et al., 2008). For an RGB-D camera, \( f(q) \) has a cone shape with center \( c(q) \), opening angle \( \alpha \), and radius \( R \). These parameters are later determined based on real-world sensor specifications. In this study, the sensor model is defined as
\[ p(z = 0 | x, q) = 1 - p_e \] if \( x \not\subset f(q) \)
\[ p(z = 0 | x, q) = 1 - p_d \] if \( x \subset f(q) \)
\[ p(z \neq 0 | x, q) = p_e \] if \( x \not\subset f(q) \)
\[ p(z \neq 0 | x, q) = p_{d - N}(z | x, \Sigma) \] if \( x \subset f(q) \)

where \( p_2 \) is a user-defined true positive probability of the detection algorithm and \( p_e \) is the false negative probability (\( e \) stands for error).

**Fig. 2** Dynamic Bayesian Network with context states \( c_k \), target states \( x_k \), and robot configurations \( q_k \). \( y_k \) and \( z_k \) are measurements for context and targets, respectively. The arrows indicate the conditional dependencies between the random variables. The dotted line indicates that when an object is missing, its target location cannot be directly estimated. In our case, it is inferred from context information.
2.5 Importance Sampling

Typically, sequential sensor observations are used to update weights of particles and compute the resulting probability distributions. However, for our active object tracking problem, continuous sensor readings are not always available due to frequently missing targets from occlusion or disappearance. To update the importance of particles, our proposed sensor model, Equation (13), is used. For example, for the case of target occlusion, the weight of particles in the field of view ($S_2(q)$) in Fig. 3 will be reduced according to the value $(1-p_d)$. On the other hand, the weights of particles outside the FOV ($S_1(q)$) will be updated according to the value $(1-p_e)$. We use re-sampling to avoid degeneracy problems and increase efficiency.

3 Methods

3.1 Entropy to Reduce Uncertainty

The goal of active perception is to gather as much information as possible, or equivalently to reduce uncertainty. Shannon’s entropy is defined as measuring the uncertainty of a random variable. For our problem, the desired control actions (i.e., moving the robot to a new configuration) correspond to policies that reduce uncertainty the most. Using the target’s posterior distribution, $p(z|x)$, its entropy is represented as

$$H(p(x|z,q)) = \int_{x \in \Omega} -p(x|z,q) \log p(x|z,q) dx.$$  \hspace{1cm} (14)

Using eq. (7), the entropy can be approximated by the particle weights as

$$H(p(x|z,q)) = -\sum_i^N w_i \log w_i.$$ \hspace{1cm} (15)

The full set of particle weights $\Omega$ can be divided into two sets ($S_1(q_1)$, $S_2(q_k)$) based on the FOV of the sensor $f(q_k)$. Here $S_1$ denotes the set of particles within the FOV, while $S_2$ is the set of particles that are not included in the FOV. Note that the region defined by $S_1(q)$ does not belong to $f(q_k)$ since it is occluded. Mathematically, $S_1 = \{ w \in \Omega : x^i \notin f(q_k) \}$ and is disjointed from $S_2$, i.e., $S_2 = \Omega \setminus S_1$. As a result, the entropy equation can be expressed as

$$H(p(x|z_2,q_1)) \approx -\sum_{i \in S_1} w_i \log w_i - \sum_{j \in S_2} w_j \log w_j.$$ \hspace{1cm} (16)

The expected information gain (IG) only depends on the first term of the above equation, and thus can be written as

$$IG(q_k) = -E[H(x_{k-1}|z_{k-1}, q_{k-1}) - H(p(x_{k-1}|z_{k-1}, q_k))]$$

$$\approx \sum_{i \in S_1(q)} w_i \log w_i.$$ \hspace{1cm} (17)

3.2 Utility Function For Target Detection

The first term of our utility function is the information gain, which involves the amount of information that can be obtained given sampled configurations. The second term penalizes traveling cost. Lastly, we define a perception gain that assists the robot to approach targets to increase the quality of the sensing process. Mathematically, the cost function is described as

$$J(x_k, q_{k-1}, q_k) = IG - \zeta_{\text{travel}} - \zeta_{\text{perception}}.$$ \hspace{1cm} (18)

$$\zeta_{\text{travel}} = \beta(q_k - q_{k-1})^T Q(q_k - q_{k-1})$$ \hspace{1cm} (19)

$$\zeta_{\text{perception}} = \gamma(x_k - S_d q_k)^T (x_k - S_d q_k).$$ \hspace{1cm} (20)

Here $x_k$ is the estimated position of the target at time $k$, $q_{k-1}$ is the current robot configuration, $q_k$ are sampled robot configurations, $\beta$, $\gamma$ are cost weighting factors, and $S_d$ is a mapping that extracts the Cartesian position of the robot from its position-rotation configuration. Solving this cost yields,

$$q_k^* = \arg \max J(x_k, q_{k-1}, q_k)$$ \hspace{1cm} (21)

To solve this problem we use a sampling based approach and greedy search to obtain the final result, $q_k^*$.

3.3 POMDP High-level Planner

For our decision framework, we will estimate the current context and based on it choose actions to obtain rewards. Since context cannot be directly measured, our planner is formulated as a Partially-Observable Markov Decision Process (POMDP). A POMDP can be described by the tuple $(S, I, A, Z, T, R)$, a finite set of states $S = \{s_1, \ldots, s_M\}$, an initial probability distribution over these states $I$, a finite set
of actions $A = \{a_1, \cdots, a_{|A|}\}$, a finite set of observations $Z = \{o_1, \cdots, o_{|Z|}\}$, and a transition function $T(s, a, s') = P(s'|s, a)$ that maps $S \times A$ into discrete probability distributions over $S$. In detail, a transition model $T(s, a, s')$ specifies the conditional probability distribution of shifting from state $s$ to $s'$ by applying action $a$. $Z(s', a, o) = P(o|s, a)$ is the observation mapping that computes the probability of observing $o$ in state $s'$ when executing action $a$. $R = r(s', a, s)$ is the reward function.

A POMDP is equivalent to a continuous-state Markov Decision Process where the states are beliefs, also called a belief MDP (Krishnamurthy, 2016). Thus a state can be rewritten using belief states $b(s) = p(s)$, defined as the posterior distribution over all possible states given the history of actions and observations. For our purposes, the states will be the context situations. In the vein of Eqs. (1) and (2), using Bayesian formulation belief states can be represented recursively as follows:

$$b_k(s|a_{k-1}) = \sum_{s' \in S} T(s, a_{k-1}, s') b_{k-1}(s)$$  \hspace{1cm} (22)

$$b_k(s|a_{k-1}, o_k) = \eta Z(s, a_{k-1}, o_k) b_k(s|a_{k-1})$$  \hspace{1cm} (23)

where $\eta$ is a normalizing constant. The goal of the POMDP is to select a sequence of actions over time to maximize the expected cumulative reward. Value iteration algorithms are used for optimally solving POMDPs. This strategy can be defined as a policy $\pi^*$, which maps a belief $b$ to actions. Given policy $\pi$, a belief $b(s) \in B$, the value function can be computed via the Bellman equation as

$$V(b, \pi) = \rho(b, \pi(b)) + \gamma \sum_{b' \in B} \tau(b, \pi, b') V(b', \pi),$$ \hspace{1cm} (24)

where $\gamma$ is a discount factor, $\rho$ is the expected reward, and $\tau$ is the transition probability to $b'$ from $b$ under $\pi$, which can be computed as $\rho = \text{Ross et al., 2008}$.

$$\tau(b, \pi, b') = \sum_{o \in Z} p(b'|b, \pi, o) p(o|b, \pi).$$  \hspace{1cm} (25)

The best policy $\pi^*$ is obtained by solving the optimization problem:

$$\pi^*(b) = \arg \max \pi \rho V(h_k, \pi_k).$$ \hspace{1cm} (26)

In this paper, we utilize an on-line POMDP solver, the Determinized Sparse Partially Observable Tree (DESPOT) (Ye et al., 2017), to obtain the optimal action policy based on the current belief of context states.

### 3.4 POMDP Problem Formulation

#### 3.4.1 System States

System states include robot position, target position and context states. Positions of the robot and target are represented in 2D using an occupancy grid. Context states correspond to one of the following semantically grounded symbols: {Visible, Occluded, Disappearance, Irrecoverable}, some of which cannot be measured directly using sensors. Visible is the state in which the target can be directly measured by the robot’s sensors. Occluded is the state when the target has been occluded by another object but is believed to be behind it. Disappearance is the state in which the target is not directly visible by the robot and is not believed to be occluded by another object in the robot’s field of view. In this state, the target is believed to have been moved away by a person. Finally, Irrecoverable corresponds to the case when the robot does not have information about the whereabouts of the target nor it can use context information to find it.

#### 3.4.2 Actions

Our action set is defined as $A = \{\text{Track, Search, Active Move}\}$. The Track action commands the robot to track targets by either panning its head or navigating towards the target. Active Move prompts the robot to change its location to better track a visible target or to overcome Occlusion situations where the target is believed to be behind another object. Lastly Search prompts the robot to explore its environment in search of humans by turning its head. This action corresponds to the hypothesis that when an object is missing it might be around a human therefore finding humans might reveal the target. In addition, we search for humans instead of directly searching for the target, since people are larger and easier to spot from afar.

#### 3.4.3 Transitions

We define a transition model to estimate the next context state based on the available actions, i.e. $p(c_k|c_{k-1})$ as de-
fined in Equation (23). We remark that context updates are performed at asynchronous time frames since actions take more than one time step to complete. Accordingly, we define transitions as:

\[
p(e|e_{t-1}) = \begin{cases} 
  1 & \text{if } a \text{ is active} \\
  b_{t-1}(e|a_{t-1}) & \text{if } a \text{ is active,}
\end{cases}
\]  

(27)

where \( l \) is a distinct time frame from \( k \) since transitions among context states are determined based on the execution time of high-level actions. Transitions between context states are described in Fig. [4].

In order to sample possible scenarios from the current belief using an online POMDP solver such as DESPOT or POMCP \cite{Silver2010}, we define a deterministic simulative model function \( g : S \times A \times R \rightarrow S \times Z \), where a random number \( \phi \) is distributed uniformly over \([0,1]\). Then, \((s', z') = g(s, a, \phi)\) is distributed according to \( p(s', z'|s, a) = T(s, a, s')O(s', a, z').\) In our study, the observation function \( O(s', a, z')\) varies according to the combination of the sensed robot and target positions, and the occlusion status.

### 3.4.4 Observations

To estimate hidden context states, we rely on four features. The most useful feature is whether a target observation exists or not. If \( z_k \) is non-empty, the context state might be visible with high probability. Thus, the first feature variable is defined as \( \theta_{\text{target}} = 1 \) if \( z_k \) exists, otherwise, \( \theta_{\text{target}} = 0 \).

The second feature we consider reflects the probability of occlusions to occur, and can be computed by using existing object recognition algorithms. Once an occlusion occurs, the object being tracked will be occluded by another object (both of them represented by bounding boxes traced by the object recognition software). In the case that objects causing occlusions are semantically identifiable, an overlap ratio is defined based on the two bounding boxes (the object being tracked, \( i \), and the newly occluding object, \( j \)) as

\[
\text{OR}_{ij}^k = \frac{\text{BB}_{ij}^k \cap \text{BB}_{i-1,j}^k}{\text{BB}_{i-1,j}^k},
\]  

(28)

where \( \text{BB}_{ij}^k \) denotes the bounding box for object \( i \) at time index \( k \). We define a feature \( \theta_{OR} \in \{0, 1\} \) as the rule \( (\text{OR}_{ij}^k > \lambda_{OR}) \cap (z = \emptyset) \) where \( \lambda_{OR} \) is a predefined threshold and \( z = \emptyset \) denotes the absence of a target. In the case that the occluding object is unidentifiable, the depth variance can also be used to detect the occlusion. Note that the depth within the bounding box will become smaller when a new object starts occluding the previous one. Therefore, features affected by depth variation can be formulated as

\[
\Delta Z_k^i = Z_{k-\Delta T,k}^i - Z_k^i,
\]  

(29)

where \( Z_{k-\Delta T,k}^i = \frac{1}{\Delta T} \sum_{z \in Z_k} z \) denotes the average depth for time period \( \Delta T \) within BB, and \( Z_k^i \) stands for the newly detected depth value (i.e. the occluding object) for the same region. Thus, we define a feature variable for depth information as follows

\[
\theta_{\text{Depth}} = \begin{cases} 
  1 & (\Delta Z_k^i > \lambda_{\text{depth}} \cap z = \emptyset) \\
  0 & \text{otherwise.}
\end{cases}
\]  

(30)

Lastly, the loss of a target can also be inferred based on the premise that the main cause of its disappearance is a human taking it away. This assumption seemingly makes sense since most common objects cannot change their location by themselves. Accordingly, we define a new feature associate with the presence of a human as, \( \theta_{\text{human}} = 1 \) if a human is present. In practice, we detect humans by using the object recognition algorithm \cite{Redmon2016}.

Consequently, the observation model is expressed using the feature vector

\[
\Theta := (\theta_{\text{target}}, \theta_{OR}, \theta_{\text{Depth}}, \theta_{\text{human}}).
\]  

(31)

By detecting features, we estimate the context state using the likelihood distribution \( p(o|s,a) \approx p(\Theta|s) = \Pi_{k=1}^t p(\Theta|s) \) which relies on the assumption that each feature is conditionally independent.

We utilize the sensor model from subsection [24] which depends on whether the target is within the FOV or it is not. In addition, to reflect the decrease in recognition accuracy as the distance between the sensor position and target position \( d \) increases, the depth coefficient can be computed as

\[
\hat{\xi}(d) = \frac{1}{1 + \exp \beta (d - d_{\text{max}})},
\]  

(32)

where \( \beta \) denotes the slope of the reduction over depth and \( d_{\text{max}} \) is the maximum distance that targets can be recognized. This depth coefficient is multiplied by the basic feature recognition accuracy parameters \( P_d \) and \( P_e \) in the sensor model, Equation (13), for use in the observation function of DESPOT.

### 3.4.5 Rewards

We assign positive rewards only when the context state is visible otherwise we do not give rewards. As such, we compute the expected reward \( p(\cdot) \) using the belief state \( b(s) \) and the reward function \( r(s,a) \) as

\[
p(b(s), a) = \sum_s b(s) r(s,a),
\]  

(33)

\[
r(s,a) = \begin{cases} 
  \psi \ast IG(q_k) + R & \text{if } s \text{ is Visible} \\
  \psi \ast IG(q_k) & \text{otherwise}
\end{cases},
\]  

(34)

where \( \psi \) denotes the coefficient for normalizing information gain and \( R \) is the positive reward for successful re-targeting. In this study, we set the discounting factor, \( \gamma \) as 0.9.
3.5 Context Models

As indicated in Equation (6), each context state has its own prediction model regarding the target’s location given prior knowledge.

3.5.1 Visible Context

In this case, we predict the target’s position from the last target state \( x_{k-1} \) using a Gaussian distribution, i.e.

\[
p(x_k | c = \text{visible}) \approx \mathcal{N}(x_k; x_{k-1} + v_{k-1}\Delta t, \sigma_x^2)
\]

where \( \sigma_x^2 \) is the sensor noise.

3.5.2 Occluded Context

In this case, we estimate the target’s position from the fact that it is behind the occluding object’s position, \( x_{\text{occ}} \), i.e.

\[
p(x_k | c = \text{Occluded}) \approx \mathcal{N}(x_k; x_{\text{occ}} + \delta_{\text{offset}}, \sigma_{\text{occ}}^2)
\]

where \( \delta_{\text{offset}} \) is an approximate distance value such as the length of the bounding box describing the occluding object.

3.5.3 Disappearance Context

In this state, the position of the target is inferred from knowledge about nearby people. If no one is visible in the FOV, the robot will begin to look for nearby people by rotating its base and head using the \textit{search} action. Once a person has been detected, a prediction model will generate particles based on the following model,

\[
p(x_k | c = \text{Disappearance}) \approx \mathcal{N}(x_k; x_{\text{human}}, \sigma_{\text{human}}^2).
\]

4 Experimental Results

4.1 Robot Description

To validate our approach experimentally, we use the Toyota Human Support Robot (HSR), a mobile manipulator equipped with an omnidirectional mobile base and a panning and tilting head. A depth camera (Xtion, Asus) is located on top of the robot’s head to obtain an RGB-D stream, sampled with 30fps. The camera parameters for FOV are 58° H, 45° V, 70° D, which stand for the angle for horizontal, vertical, and diagonal, respectively. A laser range scanner, Hokuyo, is installed at the front bottom of the base in order to detect static and dynamic obstacles. The HSR uses two different computers, one Intel Core i7, 4th Gen with 16GB RAM is used for basic navigation functions of the
robot and another one, an Alienware Intel Core i7-7820HK, GTX 1080 laptop, is used for running object detection algorithm. Interprocess communications are handled with ROS. All the skills for robots are written as ROS actions so that initiation and termination of actions can be easily managed from a high level planner. The testing facility is the UT Austin’s Human Centered Robotics Lab. For object detection we have used YOLOv3 Redmon and Farhadi (2018). It is regarded as one of the state-of-the-art methods, because of its accuracy and speed. Retinanet Lin et al. (2017) and SSD Liu et al. (2016) are also viable algorithms for our research, but YOLOv3 has the advantage of fast inference times. During our experimentation, it was assumed that if an object exists within the camera’s FOV, it will be detected reliably through YOLOv3. Based on this reliability, the value of the true positive probability of the sensor model, \( p_d \), was set to 0.95. Our focus thereafter has been on inference of occlusions or the response of the planner when objects go missing.

4.2 Scenarios

We deal with three possible situations: 1) occlusions occur due to the interference of another object, 2) objects disappear when they are taken away by people, and 3) objects temporarily move outside of the FOV but can be quickly found by employing active tracking. Fig. 5 shows that the robot is able to track and resolve occlusion situations through searching for new configurations and successfully re-locating the target. In addition, the examples demonstrating the second and third cases above are shown in Fig. 7. Details can be found in Fig. 5. This figure provides the evolution of the estimated context states and the corresponding high-level actions taken over time based on context states.

4.3 Performance Evaluation

We propose four criteria to evaluate performance: Success Ratio (SR), Tracking Ratio (TR), Average Restoring Time (ART), and Failure Time (FT). Each criterion is evaluated over 20 trials until the robot fails to track the target. The statistical results are shown in Table 4.

| Criterion | Mean | Standard Deviation |
|-----------|------|--------------------|
| SR        | 0.82 | 0.097              |
| TR        | 0.71 | 0.096              |
| ART (s)   | 10.22| 7.9                |
| FT (s)    | 232  | 44.2               |

4.3.2 Tracking Ratio (TR)

This ratio can be regarded as keeping the target in the FOV. It is calculated using the amount of time the target is believed to be in the visible state versus the total time an experiment lasts. We achieved an average TR value of 0.7 for the demos above, i.e. a mixture of experiments where we repeatedly occluded the target, or a person moved it away to nearby locations outside of the robot’s FOV, or a person rapidly moved the target around the robot.

4.3.3 Average Restoring Time (ART)

This time is calculated as the differential of time between loosing sight of a target until it is re-located. It varies depending on the type of action. For example, the average restoring time for Track was 2 seconds while that for Active-Move was 12.15 seconds with a standard deviation of 3.95. Lastly, the ART for Search was 16.5 seconds with standard deviation of 7.8.

4.3.4 Failure Time (FT)

Lastly, we measure the amount of time it takes the robot to fail tracking or searching targets. If the target is not found within 1 minute, the robot will go into failure mode, i.e. the context state is irrecoverable. The experiment for this measurement is done based on an arbitrary mixture of context states performed by moving the target around or occluding it. The overall FT for our action sequence is 232 seconds with standard deviation of 44.2 seconds. This indicates that the proposed algorithm performs successful target tracking and searching tasks for approximately 4 minutes before becoming irrecoverable due to arbitrary user manipulations.

5 Concluding Remarks

This paper addresses active target tracking and searching capabilities using mobile robots. Experimental results are performed using multiple scene trials. To this point, we employ information-theoretic costs for active search. Integrating a DBN model, particle filtering and POMDP planning, we are able not only to infer target locations from context information in a probabilistic manner, but also to define cost functions effectively. Obtaining the desirable control inputs
Fig. 7  Demo showcasing finding a target when it suddenly disappears from the robot’s FOV and is not believed to be occluded by another object. (a) Initially, the robot tracks the target (a bottle) using its depth cameras. (b) The target suddenly disappears from its FOV; here it is believed the target has disappeared because of the information returned from the observation model described earlier. (c) The robot moves to find a person around its neighborhood. If a person is detected, the robot navigates to that person and attempts to locate the target nearby. (d) In our demo, the robot succeeds in re-locating the object since it was placed next to the person.

Fig. 8  Success ratio for various active sensing scenarios. The rates represent the ratio of success to track or find a target after action execution depending on believed context states. Track behaviors have the highest success rates, 0.88, followed by Active Move, while search has the highest variance and the lowest success rates, 0.74.

for gathering information allows our robot to have better tracking and search capabilities under several dynamic conditions, such as occlusions and the sudden disappearance of a target.

We highlight the following achievements. First, our methods are scalable and versatile via the proposed hybrid state estimator, i.e., the particle filter plus POMDP based on context states. To this point, the action sequence shown in Fig. 6 effectively demonstrates the robot’s capability to actively find occluded or missing targets under various dynamic conditions. Second, as shown in Fig. 8 our active sensing algorithm, on average, re-locates targets with high success rates. Finally, we have verified robustness and efficiency of our methods using the proposed criteria, SR, TR, ART, and FT. In essence, we verified that the robot can perform practical tracking and search tasks while operating in dynamic environments.

This paper has been focused on the estimation of objects and the control of the robot. The experiment presented was designed as a concept validation. In the future we will deploy the framework in many different scenarios to obtain statistical data for in-depth analysis. We will also be on the lookout for benchmark data-sets for “active object tracking” since to date there don’t exist. Furthermore, better probabilistic models are required to model realistic target search situations. For example, our current method assumes that direct transitions between occlusion and disappearance states do not happen. Furthermore, to deal with more realistic situations, a memory-based approach that uses historical data should be used to predict context. Recurrent Neural Networks might be a good solution for future work. Lastly, there exists a room for extending our proposed work to multi-object tracking cases.

Overall, this work demonstrates a prototype of robust autonomous active target tracking performed using a mobile robot in a practical setup.

Appendix A  Parameter Selection

For particle filtering during experimentation, there are various parameters to be determined, such as the total number of particles, re-sampling conditions (effective sample size) or type of method (residual method), motion model noise, or the sensor model. Here are the parameter list that we empirically determined for our study.
Table 3 Parameters for Particle Filter

| Parameter | Description | Value |
|-----------|-------------|-------|
| N<sub>total</sub> | Total number of particles | 2000 |
| N<sub>ESS</sub> | Effective Sample Size | 1000 |
| p<sub>T</sub> | True positive probability of detection | 0.95 |
| Σ | Variance of location | 10.0 |

Table 4 Parameters for POMDP

| Parameter | Description | Value |
|-----------|-------------|-------|
| σ<sup>x</sup> | Reward Coefficient | 0.1 |
| R | Positive Reward for finding the target | 10.0 |
| γ | Discounting factor | 0.9 |
| d<sub>max</sub> | Maximum distance for target detection | 10.0 |
| δ<sub>offset</sub> | Distance to target object from occluder | 0.35 |
| σ<sup>2</sup><sub>det</sub> | Detection noise | 0.05 |
| σ<sup>2</sup><sub>occ</sub> | Variance of occluded target location | 0.15 |
| σ<sup>2</sup><sub>human</sub> | Variance of human location | 0.5 |

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