Explicitly Task Oriented Probabilistic Active Vision for a Mobile Robot*

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Abstract. A mobile robot has always uncertainty about the world model. Reducing this uncertainty is very hard because there is a huge amount of information and the robot must focus on the most relevant one. The selection of the most relevant information must be based on the task the robot is executing, but there could be several sources of information where the robot would like to focus on. This is also true in robot soccer where the robot must pay attention to landmarks in order to self-localize and to the ball and robots in order to follow the status of the game. In the presented work, an explicitly task oriented probabilistic active vision system is proposed. The system tries to minimize the most relevant components of the uncertainty for the task that is been performed and it is explicitly task oriented in the sense that it explicitly considers a task specific value function. As a result, the system estimates the convenience of looking towards each of the available objects. As a test-bed for the presented active vision approach, we selected a robot soccer attention problem: goal covering by a goalie player.

1 Introduction

A mobile robot that is performing a task must make decisions based on information of the state of its environment and itself, often called the *world model*. Unfortunately, a mobile robot has always some degree of uncertainty in its world model. This uncertainty comes from the lack of information and the noise in the sensor measurements and the actions results. One of the key questions in mobile robotics is how to measure, reduce, and handle this uncertainty. Since this uncertainty may have a tremendous negative impact on the performance of the task that the robot is executing, one important issue is how the robot can select actions to reduce it. Active vision basically consists of executing control strategies with the purpose of improving the perception performance by focusing on the most relevant parts of the sensor information. An active vision system may control physical variables, such as gaze direction, camera parameters, etc., and/or the way data is processed such as the *region of interest* (ROI), vision methodology and parameters, resolution, etc. The relationship between perception and action has been studied in several fields apart from robotics such as neurosciences, psychology and cognitive science. For instance, experiments have showed that

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the task that a human is executing has a strong influence on his/her gaze selection [1]. This suggests that the selection of the most relevant information must be based on the task the robot is executing.

In the robot soccer domain, an autonomous robot player must estimate the state of a complex and dynamic world: it must pay attention to landmarks in order to self-localize and to the ball and robots in order to follow the status of the game. The process of estimating the absolute *pose*[1] of the robot itself from *landmark*[2] observations is known as *localization*, while the process of estimating a mobile object position from observations of the object is known as *object tracking*. A robot soccer player must perform localization and ball tracking processes simultaneously, which is a problem because these two processes require the observation of different objects to correct the odometry and observation noise.

In this work we present an explicitly task oriented approach to the active vision problem, which tries to reduce the more relevant components of the uncertainty in the world model, for the execution of the current task the robot is executing. The presented approach is explicitly task oriented because it intends to minimize the variance of a task specific *value function*[3]. The output of the system is a selected object which is the most convenient to focus on. The focus on the selected object could be subsequently achieved by means of any of the control actions already mentioned. The proposed approach is generally applicable for problems where the following assumptions hold: (i) there is an independence between the actions necessary to accomplish the task and those necessary to direct the gaze or select the vision parameters, (ii) there is a world modeling stage which uses a Bayesian filter to estimate the world state, (iii) the task been executed has a value function defined, and (iv) the system knows a priori which objects it can observe and the state belief bring some information about where they can be observed. For problems where the former independence is not present (for example, robots without neck movements), the proposed approach is not generally applicable. In such cases, an approach that considers the interdependence between actions and observations (for example POMDP's) may be better suited. Besides, even in a system where that independence holds, sometimes it is convenient to modify the body position in order to improve the perceptions. Handling these situations is beyond the scope of this paper. Regarding the state estimation, the presented system assumes that the world modeling stage is based on a Kalman filter (KF) or any of its nonlinear variants (EKF, UKF, etc.), and thus, the belief is Gaussian. However, the extension for world modeling stages based on particle filters (PF), and thus on sample-based representations of the belief, is simple. Finally, the existence of a value function is held by a wide variety of applications, since it is difficult to even make decisions without a measurement of the convenience of each state.

We test our general approach on a specific application taken from robot soccer: goal covering by a goalie player. Robot soccer is a very interesting platform for testing robotic methodologies and algorithms since it presents a challenging environment

[1] The *pose* of the robot is defined as its absolute position and orientation.
[2] A *landmark* is defined as an observable object whose absolute position is fixed and known.
[3] A *value function* is defined as a function of the world state that increases with the degree of convenience of the world state for the execution of the current task.

and complex tasks [2]. This problem makes the selected application interesting for testing the proposed approach for gaze direction selection.

The structure of the paper is as follows. First, in section 2, the related work is reviewed. Then, section 3 presents the general statement of the proposed approach, while section 4 studies a particular case taken from the robot soccer problem. In section 5, experimental results are presented and discussed. Finally, in section 6, conclusions from the presented work are drawn.

2 Related Work

The basic ideas of the active vision paradigm were introduced under different names such as: *active vision* [3], *active perception* [4], and *animate vision* [5]. The contribution of this paradigm is that it does not consider perception as a passive process but as one that could conveniently influence the control actions. A huge amount of literature has been developed regarding active vision but it is beyond the scope of this paper to survey it, so we will focus on the most pertinent parts of it.

There are works where the control actions explicitly aim to reduce uncertainty in a probabilistic fashion, but they do it "blindly" (they focus on reducing the belief entropy), and thus, they are not generally optimal from the task performance point of view. The controlled variables in these works include, for example, robot movements and/or sensor direction [6][8], camera parameters [7]. Furthermore, they are not general from the task point of view since their goal is always the uncertainty reduction itself. From our point of view, the uncertainty reduction is a means but not an end. While the optimality from the task performance point of view for continuous beliefs is not achievable using digital computers, because integrals over the belief cannot be calculated, this work presents a suboptimal approximation which approximates the continuous beliefs by discrete ones.

In the RoboCup domain, there are some published papers on active vision. One of them [9] uses the localization estimate to change the way the vision system looks for the fixed objects in the image. As a result, the mean time required to process an image is reduced with no relevant change in the detection performance. Another work builds a decision tree for decision making and gaze selection [11]. The active vision system consists of maximizing the information gain in terms of which action should be selected, which is an advantage of this system, since it is oriented to the action selection itself. However, from our point of view, the direct mapping between observations and actions (without a state estimator) and the use of a decision tree, is not able to cope with the complexity and dynamism of real mobile robot applications (including robot soccer), and then the applicability of this kind of solutions is restricted. Finally, there is a particular work [10] which also uses a value function for the active vision system but: (i) the decision that is made in that case is whether the robot should move or observe, which we believe is control decision which can have very weaker effects and less applicability than the one of in which object to focus on, since for complex tasks several objects may bring relevant information, and (ii) it is restricted to a particular application: the navigation task with sample based beliefs of the robot localization.

3 Proposed Approach

3.1 Basic Definitions

In time step k, the *world state*, $\mathbf{x}_k$, is the set of the relevant variables of the world model (robot localization, other objects position, etc.) for the robot to make decisions. Then, we can define the *state belief*, or simply the *belief*, as the probability density function (pdf) of $\mathbf{x}_k$. For any task that the robot is performing, we should be able to define a *value function* $V_k(\mathbf{x}_k)$, which tells the robot how convenient is the state $\mathbf{x}_k$ for the accomplishment of this task. Depending on the complexity of the task, $V_k(\mathbf{x}_k)$ might be obtained from simple ad-hoc heuristics or calculated from popular methods like *Markov Decision Processes* or *Reinforcement Learning*. Note that the function $V_k(\mathbf{x}_k)$ is, in general, dependent on k[4]. In the case when $V_k(\mathbf{x}_k)$ does not depend on k, the subscript can be omitted. The proposed approach assumes that the robot control system has at least three functionalities: (i) *vision*, where the camera images are processed in order to get the observation $\mathbf{z}_k$, (ii) *world modeling*, where $\mathbf{z}_k$ is used to calculate the belief, and (iii) *decision making*, where the belief is used to select the action $\mathbf{u}_{k+1}$ that the robot will execute in the next instant, in order to minimize the variance of the value function: $\mathrm{var}(V_{k+1}(\mathbf{x}_{k+1}))$.

The world modeling and decision making modules make use of the knowledge of two probabilistic models: the *process model*, $\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k, \mathbf{w}_k)$, which models the effect of the robots actions in the state transitions, and the *observation model*, $\mathbf{z}_k = h(\mathbf{x}_k, \mathbf{u}_k, \mathbf{v}_k)$, which models the relationship between the current state and the current observation. Both models consider the existence of zero-mean random noises $\mathbf{w}_k$ and $\mathbf{v}_k$ with respective covariances $\mathbf{Q}_k$ and $\mathbf{R}_k$. Also, the Jacobians of f and h functions are respectively noted as $\mathbf{F}_k$ and $\mathbf{H}_k$.

In many mobile robotics applications, the action at time k, $\mathbf{u}_k$, can be decomposed into two parts: one, $\mathbf{u}_k^{act}$, that influences f and possibly h, and other, $\mathbf{u}_k^{sense}$, that only influences h. For example, in a legged robot with a camera mounted on a mobile neck, whose neck movements does not influence the world state, $\mathbf{u}_k^{act}$ corresponds to the movements of the legs, and $\mathbf{u}_k^{sense}$ corresponds to the movements of the neck and the vision parameters selection. Defining $f(\mathbf{x}_k, \mathbf{u}_k) = f(\mathbf{x}_k, \mathbf{u}_k, 0)$, the former condition is equivalent to $f(\mathbf{x}_k, \mathbf{u}_k) = f(\mathbf{x}_k, \mathbf{u}_k^{act})$. In this case, the selection of $\mathbf{u}_k^{act}$ may be performed before that of $\mathbf{u}_k^{sense}$, and then the selected $\mathbf{u}_k^{act}$ may be known in the $\mathbf{u}_k^{sense}$ selection process. The presented approach consists of selecting $\mathbf{u}_k^{sense}$ given $\mathbf{u}_k^{act}$ known, and assuming the active vision module is not able to modify $\mathbf{u}_k^{act}$. Since

[4] An example of tasks in which V_k depends on k is when the task has a finite time horizon, because V_k might depend on how much time is still available for the task execution.

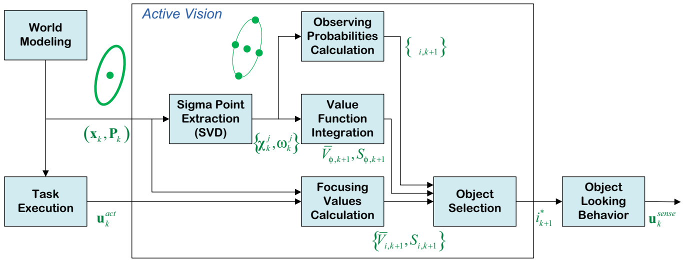

Fig. 1. Block diagram of the proposed approach for active vision (see explanations in sections 3.2-3.6)

$\mathbf{u}_k^{sense}$ cannot directly influence the future states, its main goal is to reduce the uncertainty of the state. To reduce that uncertainty in the most relevant components from the task point of view, we have selected to minimize the variance of the value function as an optimality criterion. Note that if the active vision system uses the maximization of the expected value function as an optimality criterion it will aim to be as optimistic as possible about the future values, but it does not ensure the reduction of the uncertainty.

The proposed system is designed to have as an input a Gaussian representation, $N(\bar{\mathbf{x}}_k, \mathbf{P}_k)$, of the belief. However, the system can be easily adapted to receive sample-based belief representations. The approach is based on the assumption that, given the *predicted state* $\bar{\mathbf{x}}_{k+1}^-$, each object i will have a possibly different observation noise covariance $\mathbf{R}_{k+1}^i$ [5] and naturally a different observation model jacobian $\mathbf{H}_{k+1}^i$, evaluated in the next predicted state. For each of the objects that the robot is able to look at, the variance of $V_{k+1}(\mathbf{x}_{k+1})$, given that the object will be seen in the next instant, is estimated. Then, the object with the lowest value function variance is selected, and an *object focusing behavior* executes the respective control actions, such as directing the robot gaze towards this object and/or setting the vision ROI in the object. A block diagram of the proposed active vision system may be seen in figure 1. In the next subsections, the system modules will be described.

3.2 Sigma Point Extraction

In order to make the integrals over the state space computable, the Gaussian pdf coming from the world modeling stage is transformed into a *sigma-point* pdf. A sigma point pdf is a set $\{\chi_i, \omega_i\}$ of weighted points which are sampled, from a source pdf, following some deterministic pattern which conserves the pdf's two first moments. The sigma points are calculated using the eigenvalue decomposition of the covariance

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[5] Here both $\mathbf{H}_{k+1}^i$ and $\mathbf{R}_{k+1}^i$ are at most function of i and $\bar{\mathbf{x}}_{k+1}^-$. If they are also a function of the observation $\mathbf{z}_{k+1}$, the expected observation $\mathbf{h}^i(\bar{\mathbf{x}}_{k+1}^-)$ of the i^{th} object can be considered.

matrix. The *singular value decomposition* (SVD) is used to calculate the eigenvalues decomposition[6]. The eigenvalue decomposition of $\mathbf{P}_k$ has the following form:

$$\mathbf{P}_k = \mathbf{V}_k \mathbf{\Lambda}_k \mathbf{V}_k^T \tag{1}$$

Where $\mathbf{V}_k$ is a matrix whose n^{th} column is the n^{th} eigenvector, $\mathbf{q}_{n,k}$, of $\mathbf{P}_k$, and $\mathbf{\Lambda}_k$ is a diagonal matrix whose n^{th} diagonal element is the n^{th} eigenvalue, $\lambda_{i,k}$, of $\mathbf{P}_k$. If the state space has N dimensions, the resulting sigma points are:

$$\chi_k^j = \begin{cases} \overline{\mathbf{x}}_k & j = 0 \\ \overline{\mathbf{x}}_k + \sqrt{(N+\eta)\lambda_{j,k}}\,\mathbf{q}_{j,k} & j \in [1, N] \\ \overline{\mathbf{x}}_k - \sqrt{(N+\eta)\lambda_{j-N,k}}\,\mathbf{q}_{j-N,k} & j \in [N+1, 2N] \end{cases} \tag{2}$$

We have set the scaling parameter η to 1. The corresponding weights are:

$$\omega_k^j = \begin{cases} \omega_0 = \dfrac{\eta}{(N+\eta)} & j = 0 \\ \dfrac{1}{2(N+\eta)} & \sim \end{cases} \tag{3}$$

3.3 Observing Probabilities Calculation

Let us define $\kappa_{i,k}$ and $\varphi_{i,k}$ as the events: (i) "at time k, the robot focus on the i^{th} object" and (ii) "at time k, the robot observes the i^{th} object", respectively. Note that from our definition of the problem (where $\mathbf{u}_k^{sense}$ does not influence $\mathbf{u}_k^{act}$), $\kappa_{i,k}$ does not influence $\mathbf{x}_k$, and thus $p(\mathbf{x}_k | \kappa_{i,k}) = p(\mathbf{x}_k)$. Then we can define $\alpha_{i,k}$ as the probability of $\varphi_{i,k}$ conditioned on $\kappa_{i,k}$:

$$\alpha_{i,k} = p(\varphi_{i,k} | \kappa_{i,k}) = \int_{\mathbf{x}_k \in \mathbf{X}} p(\varphi_{i,k} | \mathbf{x}_k, \kappa_{i,k}) p(\mathbf{x}_k) d\mathbf{x}_k \tag{4}$$

We can approximate the former integral using the sigma point representation $\{\chi_k^j, \omega_{j,k}\}$ of the pdf of $\mathbf{x}_k$ calculated as explained in section 3.2:

$$\alpha_{i,k} \approx \sum_{j \in [0,2N]} p(\varphi_{i,k} | \mathbf{x}_k = \chi_k^j, \kappa_{i,k}) \omega_{j,k} \tag{5}$$

The event $\varphi_{i,k}$ can be seen as the joint occurrence of three independent events: (i) $\nu_{i,k}$, "the i^{th} object is inside the field of view of the camera", (ii) $\vartheta_{i,k}$, "the i^{th} object is not been occluded by other objects", and (iii) $\rho_{i,k}$, "the camera and the vision module

[6] Since the covariance matrix is symmetric and positive semi-definite, SVD and the eigenvalue decomposition are equivalent.

with their physical limitations and current parameters are able to percept the i^{th} object". Then,

$$p(\varphi_{i,k}|\mathbf{x}_k,\kappa_{i,k}) = p(\nu_{i,k}|\mathbf{x}_k,\kappa_{i,k})p(\vartheta_{i,k}|\mathbf{x}_k,\kappa_{i,k})p(\rho_{i,k}|\mathbf{x}_k,\kappa_{i,k}) \tag{6}$$

$p(\nu_{i,k}|\mathbf{x}_k,\kappa_{i,k})$ can be calculated using the space configuration of the objects and the robot. $p(\vartheta_{i,k}|\mathbf{x}_k,\kappa_{i,k})$ can be estimated using both the robot pose and the object position plus some estimation of the probability that another object is between them. Finally, $p(\rho_{i,k}|\mathbf{x}_k,\kappa_{i,k})$ can be estimated as a function of the distance between the i^{th} object and the robot, and the parameters of the camera and the vision module.

3.4 Value Function Integration

Let us define ϕ_k as the event "no object is observed at instant k". Then, given ϕ_k, $\mathbf{P}_k$ will suffer no correction and thus the expected value of the state pdf will remain unaltered. For the calculation of the variances, we will use the well known property:

$$\text{var}(X) = S - E(X)^2 \; ; \; S = E(X^2) \tag{7}$$

The means of the value function and its square can be calculated as:

$$\overline{V}_{\phi,k} = \int_{\mathbf{x}_k \in \mathbf{X}} V_k(\mathbf{x}_k) p(\mathbf{x}_k|\phi_k) d\mathbf{x}_k \; ; \; S_{\phi,k} = \int_{\mathbf{x}_k \in \mathbf{X}} V_k(\mathbf{x}_k)^2 p(\mathbf{x}_k|\phi_k) d\mathbf{x}_k \tag{8}$$

Again, we can approximate the integrals using the sigma point representation $\{\chi_{j,k},\omega_{j,k}\}$ of the pdf of $\mathbf{x}_k$ that was calculated as detailed in section 3.2.:

$$\overline{V}_{\phi,k} \approx \sum_{j\in[0,2N]} V_k(\chi_k^j)\omega_{j,k} \; ; \; S_{\phi,k} \approx \sum_{j\in[0,2N]} V_k(\chi_k^j)^2 \omega_{j,k} \tag{9}$$

3.5 Focusing Values Calculation

Let us define a *candidate object* as one that the robot can focus on by only modifying $\mathbf{u}_k^{sense}$. For every candidate object, we can define its *focusing value variance* as the value function variance after focusing on it:

$$\sigma_{i,k}^V = \text{var}(V_k(\mathbf{x}_k)|\kappa_{i,k}) \tag{10}$$

For every candidate object, its focusing value variance is estimated, following the procedure shown in Figure 2 and detailed afterwards, in order to test the utility of focusing on that object.

Perception Simulation (i^{th} object). In order to estimate $p(\mathbf{x}_{k+1}|\varphi_{i,k+1})$, a perception $\mathbf{z}_{k+1}^i$ of the i^{th} object is simulated as the expected one. The predicted state $\overline{\mathbf{x}}_{k+1}^-$ and

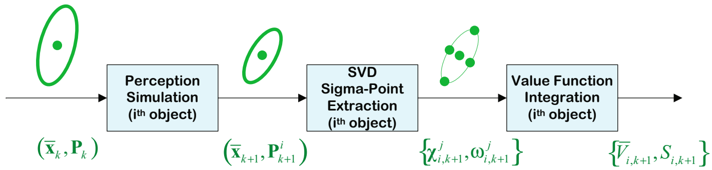

Fig. 2. The stages of the focusing values calculation process

covariance $\mathbf{P}^-_{k+1}$ should come from a prediction stage. As previously stated, $\mathbf{u}^{act}_k$ is selected before $\mathbf{u}^{sense}_k$, and thus, it is known in advance.

$$\overline{\mathbf{x}}^-_{k+1} = f\left(\overline{\mathbf{x}}_k, \mathbf{u}^{act}_k\right); \;\; \mathbf{P}^-_{k+1} = \mathbf{F}_{k+1}\mathbf{P}_k\mathbf{F}^T_{k+1} + \mathbf{Q}_{k+1} \tag{11}$$

The correction stage of the state estimate has the following form:

$$\overline{\mathbf{x}}^i_{k+1} = \overline{\mathbf{x}}^-_{k+1} + \mathbf{K}^i_{k+1}\left(\mathbf{z}^i_{k+1} - \mathbf{h}^i\left(\overline{\mathbf{x}}^-_{k+1}\right)\right) \tag{12}$$

Where $\mathbf{K}^i_{k+1}$ is the Kalman gain given $\varphi_{i,k+1}$:

$$\mathbf{K}^i_{k+1} = \mathbf{P}^-_{k+1}\left(\mathbf{H}^i_{k+1}\right)^T\left(\mathbf{H}^i_{k+1}\mathbf{P}^-_{k+1}\left(\mathbf{H}^i_{k+1}\right)^T + \mathbf{R}^i_{k+1}\right)^{-1} \tag{13}$$

Simulating the observation as the expected one means $\mathbf{z}^i_{k+1} = \mathbf{h}^i\left(\overline{\mathbf{x}}^-_{k+1}\right)$, and then the corrected state estimate is independent of *i*:

$$\overline{\mathbf{x}}^i_{k+1} = \overline{\mathbf{x}}^-_{k+1} = \overline{\mathbf{x}}_{k+1} \tag{14}$$

Thus, the state estimate remains unaltered and only the state covariance is corrected. We can calculate the state covariance given $\varphi_{i,k+1}$:

$$\mathbf{P}^i_{k+1} = \left(\mathbf{I} - \mathbf{K}^i_{k+1}\mathbf{H}^i_{k+1}\right)\mathbf{P}^-_{k+1} \tag{15}$$

Sigma Point Extraction (i^th^ object). Following the procedure detailed in section 3.2, a sigma point representation $\left\{\chi^j_{i,k+1}, \omega^j_{i,k+1}\right\}$ is calculated from the Gaussian representation $\left(\overline{\mathbf{x}}_{k+1}, \mathbf{P}^i_{k+1}\right)$ of $p\left(\mathbf{x}_{k+1} \middle| \varphi_{i,k+1}\right)$.

Value Function Integration (i^th^ object). Following the procedure detailed in section 3.4, the desired means are approximated using the sigma point representation $\left\{\chi^j_{i,k+1}, \omega^j_{i,k+1}\right\}$ of $p\left(\mathbf{x}_{k+1} \middle| \varphi_{i,k+1}\right)$:

$$\overline{V}_{i,k+1} \approx \sum_{j\in[0,2N]} V_{k+1}\left(\chi^j_{i,k+1}\right)\omega^j_{i,k+1}\,; \;\; S_{i,k+1} \approx \sum_{j\in[0,2N]} V_{k+1}\left(\chi^j_{i,k+1}\right)^2 \omega^j_{i,k+1} \tag{16}$$

3.6 Object Selection

Finally, the object i^*_{k+1} to which the robot will focus on is selected,

$$i^*_{k+1} = \arg\min_i \sigma^V_{i,k+1} \tag{17}$$

Applying the total probabilities theorem, we get the following equation:

$$p(\mathbf{x}_k|\kappa_{i,k}) = p(\mathbf{x}_k|\varphi_{i,k},\kappa_{i,k})p(\varphi_{i,k}|\kappa_{i,k}) + p(\mathbf{x}_k|\sim\varphi_{i,k},\kappa_{i,k})p(\sim\varphi_{i,k}|\kappa_{i,k}) \tag{18}$$

We assume that given $\kappa_{i,k}$ no other object is observed, then,

$$p(\mathbf{x}_k|\sim\varphi_{i,k},\kappa_{i,k}) = p(\mathbf{x}_k|\phi_k,\kappa_{i,k}) \tag{19}$$

Besides, given ϕ_k or $\theta_{i,k}$, $\kappa_{i,k}$ brings no additional information about $\mathbf{x}_k$, then,

$$p(\mathbf{x}_k|\kappa_{i,k}) = p(\mathbf{x}_k|\varphi_{i,k})\alpha_{i,k} + p(\mathbf{x}_k|\phi)(1-\alpha_{i,k}) \tag{20}$$

Now, from equations (10), (7), (9), (16), and (20),

$$\sigma^V_{i,k+1} = \left(S_{i,k+1}\alpha_{i,k+1} + S_{\phi,k+1}(1-\alpha_{i,k+1})\right) - \left(\overline{V}_{i,k+1}\alpha_{i,k+1} + \overline{V}_{\phi,k+1}(1-\alpha_{i,k+1})\right)^2 \tag{21}$$

4 Case Study: Goal Covering by a Goalie Player

With the purpose of showing the applicability of the proposed approach the robot soccer problem of goal covering by a goalie player is studied in this section. One key task that a goalie must follow is the *goal covering* task, which consists of maintaining its own position between the ball and the own goal (see fig. 3).

For the goal covering task, $V(\mathbf{x}_k)$ is independent of the instant *k*, and is defined as:

$$V(\mathbf{x}_k) = 1 - \frac{\beta_k}{\pi} \tag{22}$$

Where the *free goal angle* β_k corresponds to the maximum angle, defining an origin in the position of the ball, in which the own goal is not obstructed (see figure 3). Our selected $\mathbf{u}_k^{act}$ for this task consists of positioning the robot over the bisector of

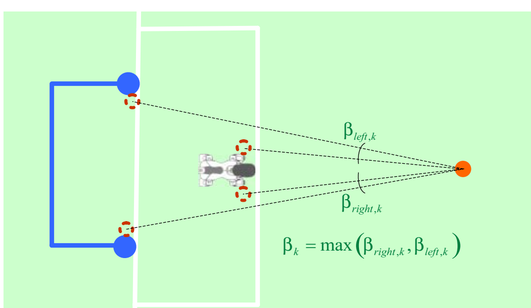

Fig. 3. Geometry of the goal covering task

the goal angle from the ball. Then, the potential attacker has two equal free goal angles to each side of the robot. The goalie must select then, to which distance d^* from the goal it should position itself. There is always a minimum distance $d_{\beta_k=0}^{\min}$ from the goal where the goalie can position to make $\beta_k = 0$. We will call $d_{zone}^{\max}$ the maximum distance to the goal where the goalie is still inside its goal zone. Then, we will select $d^* = \min\left(d_{\beta_k=0}^{\min}, d_{zone}^{\max}\right)$ to add the restriction that the goalie should keep inside its goal zone. Note that both $d_{\beta_k=0}^{\min}$ and $d_{zone}^{\max}$ depend on the absolute pose $\mathbf{G}_k = \left(G_{x,k}, G_{y,k}, G_{\theta,k}\right)$ of the goalie, and position $\mathbf{B}_k = \left(B_{x,k}, B_{y,k}\right)$ of the ball.

Then, for the goal covering task, the state of the world may be defined as $\mathbf{x}_k = \left(\mathbf{G}_k, \tilde{\mathbf{B}}_k\right)$, where $\tilde{\mathbf{B}}_k = \left(\tilde{B}_{x,k}, \tilde{B}_{y,k}\right)$ is the position of the ball with respect to the goalie. This definition of $\mathbf{x}_k$, which uses $\tilde{\mathbf{B}}_k$ instead of $\mathbf{B}_k$, is convenient from the world modeling point of view, since $\mathbf{G}_k$ may be estimated using observations of the existent landmarks and $\tilde{\mathbf{B}}_k$ may be estimated using observations of the ball. From these definitions, the localization and ball tracking processes are independent each other, which is not a requisite but is convenient for the simplicity of the problem formulation. Note that for the calculation of β_k, it is necessary to calculate:

$$\mathbf{B}_k = Rot\left(G_{\theta,k}\right)\tilde{\mathbf{B}}_k + \left(G_{x,k}, G_{y,k}\right) \tag{23}$$

Where $Rot(\theta)$ the rotation matrix in angle θ. We will define the observation of the i^{th} object as its relative to the robot position in polar coordinates, i.e., $\mathbf{z}_k^i = \left(\mathbf{z}_{r,k}^i, \mathbf{z}_{\theta,k}^i\right)$. Then, the observation model for the i^{th} object is:

$$\mathbf{h}^i(\mathbf{x}_k) = \left(\sqrt{\left(\tilde{O}_{x,k}^i\right)^2 + \left(\tilde{O}_{y,k}^i\right)^2}, \arctan\left(\tilde{O}_{y,k}^i / \tilde{O}_{x,k}^i\right)\right) \tag{24}$$

With

$$\tilde{\mathbf{O}}_k^i = \left(\tilde{O}_{x,k}^i, \tilde{O}_{y,k}^i\right) = \begin{cases} Rot\left(-G_{\theta,k}\right)\left(\mathbf{O}_k^i - \left(G_{x,k}, G_{y,k}\right)\right) & i \text{ is a landmark} \\ \tilde{\mathbf{B}}_k & i \text{ is the ball} \end{cases} \tag{25}$$

Where, $\mathbf{O}_k^i$ is the fixed and known absolute position of the i^{th} object. Then,

$$\mathbf{H}_k^i = \frac{\partial \mathbf{h}^i}{\partial \mathbf{x}_k}(\mathbf{x}_k) = \begin{cases} \begin{bmatrix} \left[\dfrac{\partial \mathbf{h}^i}{\partial \mathbf{G}_k}(\mathbf{G}_k)\right] & \begin{matrix} 0 & 0 \\ 0 & 0 \end{matrix} \end{bmatrix} & i \text{ is a landmark} \\ \begin{bmatrix} \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} & \left[\dfrac{\partial \mathbf{h}^i}{\partial \tilde{\mathbf{B}}_k}\left(\tilde{\mathbf{B}}_k\right)\right] \end{bmatrix} & i \text{ is the ball} \end{cases} \tag{26}$$

The calculation of the Jacobians is not detailed for space restrictions. In the next section, the results of simulated experiments for this application are presented.

5 Results and Discussion

In this section, we will show the applicability of the presented active vision method by testing it in the goal covering task. In this particular implementation, the active vision system acts only on the gaze direction.

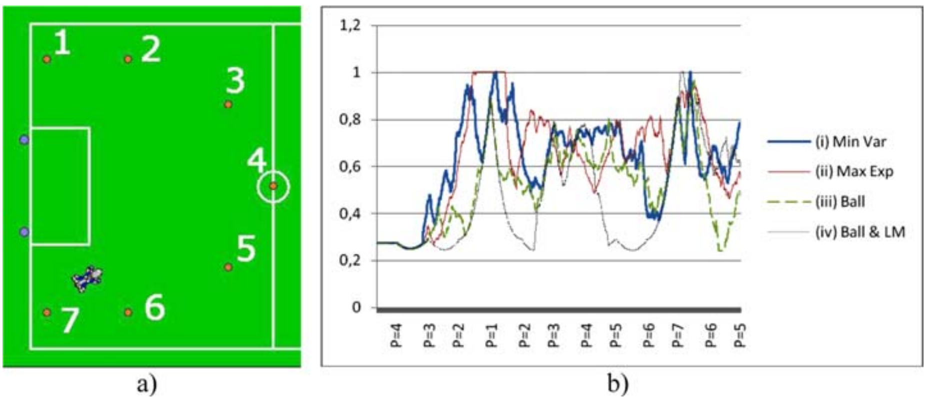

Fig. 4. Performed experiment: a) initial position of the goalie and cyclic positions (1 to 7) of the ball. b) Evolution of $V(\mathbf{x}_k)$ in the first experiment cycle, for the presented method and the compared heuristics (See posterior description of the (i)-(iv) indexes). In the horizontal axis, P=*j* represents an instant when the ball is on point *j*.

The experiment showed in this section has been performed in a high level simulator, which simulates the world modeling and decision making process and takes into account process and observation noises and observation probabilities. Only the goalie and the ball are inside the field. The goalie executes the goal covering task for a period of time of around 1 minute, while the ball rolls cyclically (4 repetitions) among 7 fixed positions. Figure 4.a shows the initial position of the goalie and the intermediate positions of the ball. Figure 4.b shows the evolution of $V(\mathbf{x}_k)$ over time.

The selected performance measures are the average and standard deviation of the actual value, $V(\mathbf{x}_k)$, evaluated in the actual state (unknown for the robot). The presented method (i) is compared to: (ii) the same method using the maximum expectation of $V(\mathbf{x}_k)$ as the optimality criterion; and two heuristics: (iii) looking always to the ball, and (iv) alternating for fixed periods (2 seconds) from the ball to a randomly selected landmark. The average and standard deviation of the actual values are respectively: 0.67 ± 0.14 for the presented method (i), 0.66 ± 0.15 for optimality criterion (ii), 0.57 ± 0.16 for heuristic (iii), and 0.62 ± 0.19 for heuristic (iv).

6 Conclusions

We have presented a probabilistic and explicitly task oriented active vision system which is able to select in which object the robot should focus. The applicability of the system is very wide from the point of view of the executed task. A particular robot soccer application, the goal covering task, is selected for showing this applicability. Preliminary results show that the presented method has a better performance in this task that some selected heuristics. As a future work, we plan to allow the system to consider the possibility of focusing in more than one object with the same sensing action, for example when the field of view of the camera is able to show more than one object of interest. We also plan to apply a similar reasoning structure to solve the problem of decision making.

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