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Combined Trajectory Planning and Gaze Direction Control for Robotic Exploration

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Abstract— **In this paper, a control scheme that combines trajectory planning and gaze direction control for robotic exploration is presented. The objective is to calculate the gaze direction and simultaneously plan the trajectory of the robot over a given time horizon, so that localization and map estimation errors are minimized while the unknown environment is explored. Most existing approaches perform a greedy optimization for the trajectory generation only over the next time step and usually neglect the limited field of view of visual sensors and consequently the need for gaze direction control. In the proposed approach an information-based objective function is used, in order to perform multiple step planning of robot motion, which quantifies a trade-off between localization, map accuracy and exploration. Relative entropy is used as an information metric for the gaze direction control. The result is an intelligent exploring mobile robot, which produces an accurate model of the environment and can cope with very uncertain robot models and sensor measurements.**

I. INTRODUCTION

In order to enable mobile robots to be used in practical application fields such as entertainment, human care, industry, etc. their cognitive capabilities must be extended. One such fundamental capability, is the autonomous acquisition of accurate models of unknown environments. To achieve that, a robot must be able to control its movement and its perception system so that it collects the highest amount of information possible, allowing it to localize itself in its environment and at the same time create a representation of this environment. Especially for robots with vision-based, active perceptual systems, such as most service, industrial and humanoid robots, this becomes equivalent to combining their motion trajectory planning with gaze direction control in order to autonomously solve a Simultaneous Localization and Mapping (SLAM) problem.

In this paper, an algorithm for combining trajectory planning and gaze direction control for SLAM is presented. The objective of the algorithm is to calculate the gaze direction and simultaneously plan the trajectory of the robot over a given time horizon, so that estimation errors are minimized while the unknown environment is explored. Most existing approaches perform an optimization only over the next time step for the trajectory generation. This is a purely local, greedy optimization. The limited field of view of visual sensors and consequently the need for gaze direction control is usually neglected. In this approach an information-based objective function is used, in order to perform multiple step planning of robot motion, which quantifies a trade-off between localization, map accuracy and exploration. Relative entropy is used as an information metric for the gaze direction control. The result is an intelligent exploring mobile robot, which produces an accurate model of the environment.

Through this novel algorithm the robot with its active sensor system anticipates all possible trajectories and viewing angles over a specific time horizon. Therefore it can cope with very uncertain robot models, such as those of humanoid robots. Moreover the algorithm performs better than other existing approaches when it comes to sensors which have a limited field of view.

Simulation results presented in Section V show, that controlling a mobile robot and its active vision system with the proposed approach, significantly increases SLAM accuracy in comparison with existing greedy approaches. The algorithm is shown to keep uncertainty under control in open-loop scenarios. A more accurate environmental model increases robot independence, therefore allowing the robot to perform more complex autonomous tasks.

The remainer of this paper is organized as follows: In Section II related work done in the fields of active vision, SLAM and robot exploration is reviewed. In Section III the Extended Kalman Filter (EKF) SLAM algorithm is briefly presented. The proposed trajectory and gaze direction control scheme is analyzed in Section IV and based on simulation results, in Section V, its performance is demonstrated and compared with greedy approaches and others that neglect gaze direction control. Finally a conclusion is given and directions of future work are discussed.

II. RELATED WORK

The problem of SLAM is one of the fundamental problems in robotics and has been studied extensively over the last years. Many solutions exist [1]–[3], only to mention some popular ones. However this work focuses on the aspects of state estimation, belief representation and belief update using prerecorded sensor data, without dealing with how such data can autonomously be gathered by the robot.

The field of robotic exploration deals with this challenge. As mentioned before, most existing approaches choose the next position of the robot based on a greedy optimization of information gain [4]–[6], ignoring the need for planning the

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trajectory of the robot over longer time horizons. An interesting planning approach which introduces a new measure of map quality is described in [7], but it assumes some initial state estimate of all the landmarks and the limited field of view of the sensors is not taken into account. Active sensor control is also not considered. Another multi-step planning algorithm for SLAM is described in [8] which makes use of concepts from the field of model predictive control, including a discussion about the necessity of trajectory planning. But again the aim is at steering the robot, without an active sensor system and only very few simulation results are presented. In [9] simulated results are presented which demonstrate the effect of different actions to information gain, while unmanned aerial vehicles perform SLAM based on cameras.

Very interesting work has also been done in the field of active vision. In [10] and [11] the SLAM problem has been solved with active visual sensing, but the main focus of these works was on feature selection. A control strategy for performing SLAM with a single camera carried by a human has been analyzed in [12]. Finally [13] introduces a gaze direction strategy for localization and obstacle avoidance for humanoid robots but once again this is a greedy approach and mapping is not taken into account. In all of these works, controlling the visual sensors is decoupled from motion control.

III. EXTENDED KALMAN FILTER SLAM

As mentioned before, several SLAM algorithms have been introduced over the last years. Although more computationally efficient algorithms exist, a Kalman filter-based approach was chosen as a basis for the proposed algorithm, because of its representational ability and approximation quality. It provides a recursive solution to the navigation problem and at the same time consistent uncertainty estimates for robot and landmark positions, which can be used to infer how the model estimate can be improved by different actions. A brief overview of the EKF SLAM algorithm will be given in this section, more detailed analysis can be found in [1], [5].

The state of the robot is $\boldsymbol{x}_r = [x_r, y_r, \phi_r]^T$, with x_r, y_r denoting its position and ϕ_r its orientation. The control input of the vehicle is given by $\boldsymbol{u} = [u_x, u_y, u_\phi]$. The motion model of the robot is described by

$$\boldsymbol{x}_{r_{k+1}} = \boldsymbol{f}(\boldsymbol{x}_k, \boldsymbol{u}_k) + \boldsymbol{G}(\boldsymbol{u}_k)\boldsymbol{d}_x, \tag{1}$$

where $\boldsymbol{G}(\boldsymbol{u}_k)$ scales the process noise $\boldsymbol{d}_x$ as a function of the distance traveled. The process noise is Gaussian with covariance $\boldsymbol{Q}$ and function $\boldsymbol{f}$ depends on the robot type.

The location of each environmental feature is denoted by $\boldsymbol{p}_i$ and they are assumed stationary. The augmented state vector containing both the state of the robot and the state of all landmarks can be written as:

$$\boldsymbol{x}_k = [\boldsymbol{x}_{r_k}^T \boldsymbol{p}_1^T \dots \boldsymbol{p}_N^T]^T. \tag{2}$$

The active sensor observations are described by

$$\boldsymbol{z}_k = \boldsymbol{h}(\boldsymbol{x}_k, \boldsymbol{s}_k) + \boldsymbol{d}_z, \tag{3}$$

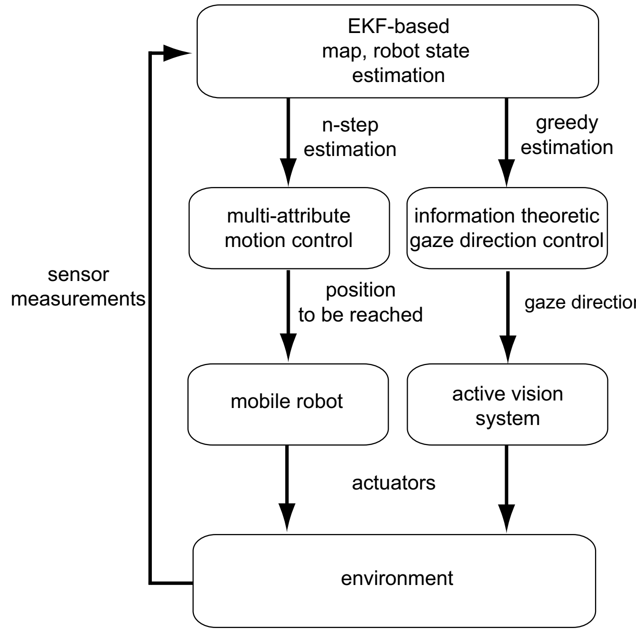

Fig. 1. Proposed motion and gaze direction control scheme

with $\boldsymbol{z}_k$ the observation vector of range and bearing measurements. The observation matrix, $\boldsymbol{h}$, relates the output of the sensors to the state vector $\boldsymbol{x}_k$, when observing the features. With $\boldsymbol{s}_k$ the control input of the active visual sensor is denoted, which in this paper is supposed to consist of turning angles for the active cameras and $\boldsymbol{d}_z$ is the Gaussian observation noise with covariance $\boldsymbol{R}_k$.

The Kalman filter algorithm begins with a prediction step. The knowledge of estimate $\hat{\boldsymbol{x}}_{k|k}$ of the state and the state covariance matrix $\boldsymbol{P}_{k|k}$ at time t_k, are assumed. Now, a prediction for the state, the state covariance and the observations at time $k+1$ can be generated as

$$\hat{\boldsymbol{x}}_{k+1|k} = \boldsymbol{f}(\boldsymbol{x}_{k|k}, \boldsymbol{u}_k) \tag{4}$$

$$\hat{\boldsymbol{z}}_{k+1|k} = \boldsymbol{h}(\boldsymbol{x}_{k|k}, \boldsymbol{s}_k) \tag{5}$$

$$\boldsymbol{P}_{k+1|k} = \boldsymbol{F}_x \boldsymbol{P}_{k|k} \boldsymbol{F}_x^T + \boldsymbol{F}_d \boldsymbol{Q} \boldsymbol{F}_d^T \tag{6}$$

where $\boldsymbol{F}_x = \nabla_x \boldsymbol{f}|_{(\hat{\boldsymbol{x}}_{k+1|k}, \boldsymbol{u}_k)}$ is the Jacobian of the state transition function and $\boldsymbol{F}_d = \nabla_{d_x} \boldsymbol{G}(\boldsymbol{u}_k)\boldsymbol{d}_x$ is the Jacobian of the noise input $\boldsymbol{d}_x$.

Following the prediction, an observation is being made according to (3). Correct landmark association is assumed. The difference between the actual and the predicted observation can be calculated, which is called innovation, from

$$v_{k+1} = \boldsymbol{z}_{k+1} - \hat{\boldsymbol{z}}_{k+1|k} \tag{7}$$

The innovation covariance is

$$\boldsymbol{S}_{k+1} = \boldsymbol{H}_x \boldsymbol{P}_{k+1|k} \boldsymbol{H}_x^T + \boldsymbol{R}_{k+1} \tag{8}$$

with $\boldsymbol{H}_x = \nabla_x \boldsymbol{h}|_{(\hat{\boldsymbol{x}}_{k+1|k}, \boldsymbol{s}_k)}$.

Finally the state estimate is updated

$$\hat{\boldsymbol{x}}_{k+1|k+1} = \hat{\boldsymbol{x}}_{k+1|k} + \boldsymbol{W} v_{k+1}, \tag{9}$$

as well as the state estimate covariance

$$\boldsymbol{P}_{k+1|k+1} = \boldsymbol{P}_{k+1|k} - \boldsymbol{W}\boldsymbol{S}_{k+1}\boldsymbol{W}^T \tag{10}$$

with $\boldsymbol{W} = \boldsymbol{P}_{k+1|k}\boldsymbol{H}^T\boldsymbol{S}_{k+1}^{-1}$ being the Kalman gain matrix.

Using the SLAM algorithm described in this section, allows a robot to build a map from sensor data and localize itself in it. The challenge is to find a way to collect the necessary sensor data autonomously in order to build the most precise map and at the same time explore the environment as actively as possible. In the next section this challenge will be analyzed and a solution will be proposed.

IV. EXPLORATION STRATEGY

Fig. 1 illustrates the proposed motion and gaze direction control scheme. The robot and its active vision system are controlled by two modules which use a common model of the environment. For the trajectory planning a multi-step estimation algorithm is used to evaluate all possible positions that can be reached by the robot over a finite, given time horizon. This estimation forms a multi-attribute function which is used to decide where the robot should move next. A trade-off is made between localization, map accuracy and the proactivity of the exploration. For the gaze direction control a greedy information-based optimization is used to choose the view that minimizes position and map uncertainties. All the components of the proposed approach will be examined in detail.

A. Gaze Direction Control

In the case of vision guided robots optimal use of the sensory resources, means correctly deciding the next view direction, so that measurements are obtained which are most informative about the state of the environment. This raises the question of how to measure information gain.

1) Measuring Information: A commonly used measure of uncertainty is entropy which has been introduced by Shannon [14]. The entropy of a discrete random variable x, on a finite set X and with probability distribution function $p(x)$ is defined as:

$$H(p(x)) = -\sum_X p(x)\log p(x) \tag{11}$$

which in the case of a multivariate Gaussian distribution $p(x)$ with covariance $\boldsymbol{P}$, can be shown [15] that is equal to $H(p(x)) = \frac{1}{2}\log((2\pi e)^n|\boldsymbol{P}|)$. Since the determinant of a matrix is a measure for its volume, the entropy measures the compactness and thus the informativeness of a distribution.

In order to measure the utility of a gaze direction which will result to an observation $\boldsymbol{z}$, the mutual information gain $I[\boldsymbol{x},\boldsymbol{z}]$ will be used. The gain in information between any two distributions can be computed as the change in entropy. Here, these are the state estimates before and after making an observation, which are both multivariate Gaussians with covariances $\boldsymbol{P}_{k+1|k}$ and $\boldsymbol{P}_{k+1|k+1}$. Therefore it is equal to

$$\begin{aligned} I[\boldsymbol{x},\boldsymbol{z}] &= H(\boldsymbol{x}) - H(\boldsymbol{x}|\boldsymbol{z}) \\ &= \frac{1}{2}\log|\boldsymbol{P}_{k+1|k}| - \frac{1}{2}\log|\boldsymbol{P}_{k+1|k+1}|. \end{aligned} \tag{12}$$

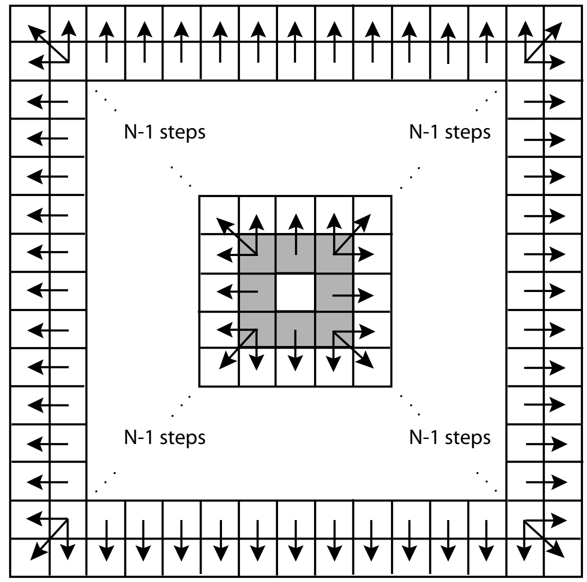

Fig. 2. Region covered while planning over a horizon of N steps. The arrows indicate which predicted states and covariances are used in each step in order to calculate the values for the next step of the planning algorithm. Highlighted grid cells show which cells are taken into account for gaze direction control

Information gain can be calculated only as a function of the state covariance matrix. Maximizing information gain is equivalent to choosing actions that reduce the uncertainty of the state estimate, due to the measurements that are received. From (12) it is obvious that $I[\boldsymbol{x},\boldsymbol{z}]$ becomes maximum, when the determinant of $\boldsymbol{P}_{k+1|k+1}$ is minimized.

2) Deciding the Gaze Direction: At each time step the number of features that are visible by the robot depends on the field of view of the perceptual system and their relative locations to the robot, at the time of observation. Since no knowledge of future movements is assumed, all the positions that can be reached by the robot over the next time step have to be taken into account. Starting from the currently estimated state the first eight neighboring states that can be observed by the vision sensors and their covariances are predicted, according to (4)-(6). In Fig. 2 these states are illustrated gray. After all state covariances are estimated, the most informative state can be calculated, which as can be seen from (12) is the one that minimizes $|\boldsymbol{P}_{k+1|k+1}|$. The control input of the active visual sensors $\boldsymbol{s}_{k+1}$ is then computed so that the active vision system is directed towards this position. Next, the motion planning component of the proposed control scheme will be introduced.

B. Motion Planning

As mentioned before, the first step for choosing the next destination for the robot is to predict the states and covariances of all possible positions that can be reached over its planning horizon. A discretized grid environment is used, where each grid represents a position that can be reached by the robot over future time steps. The size of the grid cells depends on the maximum distance that the robot can travel until the next motion control arrives. Based on this discretized environment, the most informative location that can be reached over the planning horizon is calculated. The robot is then called to reach this position. While the robot moves, observations are made and they are used to update the state estimate. This way all available information is being used.

More specifically, based on an initial state estimate $\hat{\boldsymbol{x}}_{0|0}$ and covariance matrix $\boldsymbol{P}_{0|0}$ all possible robot states and their covariance after N time steps are predicted. To achieve that the extended Kalman filter is used, which was presented in Section III. A mathematical description of the algorithm follows, where the same mathematical formalism with the previous section is kept.

For each step k = 1 to N do

For each possible state i = 1 to $8k$ *calculate*

$$\begin{aligned}
\hat{\boldsymbol{x}}^i_{k|k} &= \boldsymbol{f}(\hat{\boldsymbol{x}}^j_{k-1|k-1}, \boldsymbol{u}^j_{i,k}) \\
\boldsymbol{P}^i_{k|k-1} &= \boldsymbol{F}_{x_j}\boldsymbol{P}^j_{k-1|k-1}\boldsymbol{F}^T_{x_j} + \boldsymbol{F}_d\boldsymbol{Q}\boldsymbol{F}^T_d \\
\boldsymbol{S}^i_k &= \boldsymbol{H}^j_k\boldsymbol{P}^i_{k|k-1}\boldsymbol{H}^{jT}_k + \boldsymbol{R}_k \\
\boldsymbol{W}^i_k &= \boldsymbol{P}^i_{k|k-1}\boldsymbol{H}^{jT}_k\boldsymbol{S}^{(i)-1}_k \\
\boldsymbol{P}^i_{k|k} &= \boldsymbol{P}^i_{k|k-1} - \boldsymbol{W}^i_k\boldsymbol{S}^i_k\boldsymbol{W}^{iT}_k
\end{aligned} \tag{13}$$

End of inner loop

End of outer loop

The prediction procedure evolves in a square-like manner, as can be seen in Fig. 2. Starting from the currently estimated state the first eight neighboring states and covariances are calculated. It must be noted here, that the first step of the planning algorithm is equivalent with the greedy approach. During the following steps the predicted state $\hat{\boldsymbol{x}}^j_{k-1|k-1}$ and covariances $\boldsymbol{P}^j_{k-1|k-1}$ of the neighboring grid cells are used to infer the next ones $\hat{\boldsymbol{x}}^i_{k|k}$, $\boldsymbol{P}^i_{k|k}$ until step N. By always using the nearest neighbor in the estimation process, estimation error is kept minimal. Over each time step k, $8k$ new states are calculated. The control signal in order to drive the robot from state j to state i, at step k is denoted by $\boldsymbol{u}^j_{i,k}$ and is chosen as indicated by the arrows in Fig. 2.

The covariance matrix $\boldsymbol{P}^i_{k|k}$ of a possible target position, as estimated by the multi-step prediction algorithm, can be written as [1]

$$\boldsymbol{P}^i_{k|k} = \begin{pmatrix} \boldsymbol{P}^i_{uu} & \boldsymbol{P}^i_{um} \\ \boldsymbol{P}^i_{mu} & \boldsymbol{P}^i_{mm} \end{pmatrix}.$$

$\boldsymbol{P}^i_{uu}$ is the error covariance matrix of the robot state estimate, $\boldsymbol{P}^i_{mm}$ is the map covariance matrix of the landmark state estimates and $\boldsymbol{P}^i_{um}$ is a cross-covariance matrix between vehicle and landmark states.

Using these matrices and the concept of relative entropy mentioned in Section IV-A.1, each possible future position of the robot can be evaluated, in order to choose the appropriate target position. The destination that maximizes the function

$$V_i = \frac{1}{2}log(\frac{|\boldsymbol{P}^i_{uu}|}{|\boldsymbol{P}^0_{uu}|}) - \gamma\frac{1}{2}log(\frac{|\boldsymbol{P}^i_{mm}|}{|\boldsymbol{P}^0_{mm}|}) \tag{14}$$

must be found.

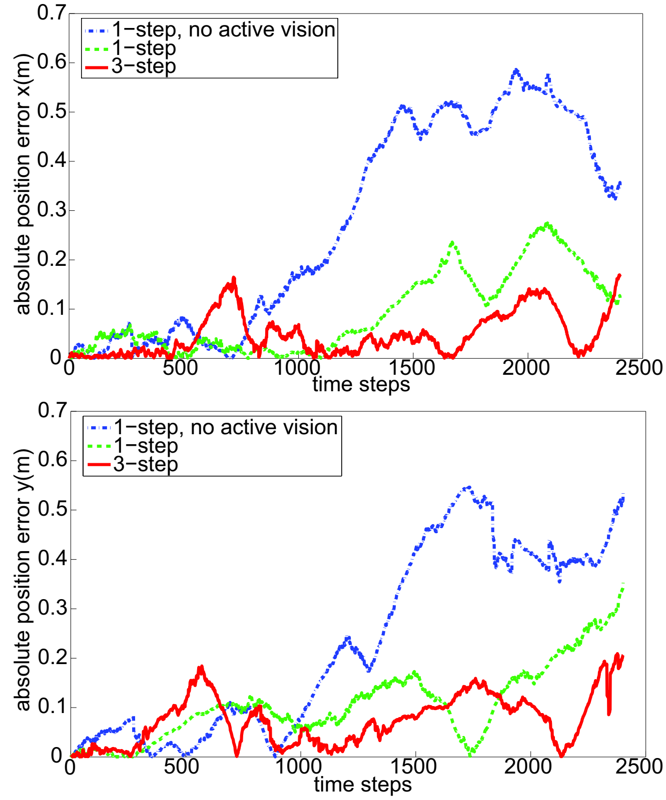

Fig. 3. Absolute position error as a function of time for a one-step planning horizon without gaze direction control and one-step, three-step planning horizons with gaze direction control

The first part of the function is a measure of the position uncertainty the robot will encounter in the future position and the second part is a measure of map quality. The constant γ can be used to adjust the behavior of the robotic explorer. Setting γ to values smaller than one, will result in a conservative exploration policy, since the robot will stay near to well-localized features giving more attention to localization. Large values of γ increase the proactivity of the explorer, in the sense that it moves to unknown areas neglecting the lower localization accuracy.

After selecting the target position that maximizes (14), the robot moves making observations which are used to update the estimated state and covariance. Each time a new state estimate is available, a recalculation of the gaze direction is made. This way all new information that become available during robot motion are used. Replanning takes place after N time steps when the target position is reached.

V. Simulation Results

The gaze direction and motion planning scheme has been described in the previous section theoretically. In order to evaluate its performance several simulations were conducted. Some results from these simulations will be presented and analysed here.

A. Simulation Description

The simulated environment consists of an area of size 40x40 meters, with randomly allocated features. The simulated active head which is mounted on top of the robot is assumed to have a field of view of 60° and a maximum viewing range of 6 meters. No initial knowledge of the environment is assumed. Feature association is considered known and all observed features are used. A harsh odometry error of 10% is chosen, since the scope of the proposed algorithm is to be able to cope with very inaccurate robot models. A sensor model with a variance proportional to the distance for bearing and range measurements is also used, with the same high noise level. The active head can be moved with high angular velocities, so that saccadic movements are simulated. Finally, γ in (14) was chosen so that the robot balances between keeping good pose estimates and exploring the environment. During simulation the robot is called to explore the area around it for 60sec based on noisy measurements received by the active sensor system.

B. Evaluation of Results

At first the visual sensors were assumed passive, directed always straight ahead of the robot, and the motion of the robot was controlled by a policy which considers only the eight neighboring states that can be reached over the next time step. This kind of policy is characterized as greedy in the literature. As can be seen in Fig. 4, only 7 features were observed and localization uncertainty is very high. So it becomes obvious that a gaze direction control strategy is necessary in this scenario.

Next, simulations were conducted with the proposed gaze direction control and again a greedy policy, followed by a simulation with a three-step planning horizon for the robot motion. In Fig. 3 the absolute position error is depicted, for all three cases. It is evident that error reduces significantly as the planning horizon for the motion of the robot grows and gaze direction control is used.

Map accuracy is illustrated in Fig. 4 through the error ellipsoids for each observed feature, for the final map. Once again it is clear that map accuracy grows as the planning horizon becomes larger. Also more features are observed when gaze direction control is used. From the final map, acquired in the case of a three-step planning horizon with gaze direction control, it becomes clear that the proposed approach balances well by observing a large number of features and also building an accurate map.

Fig. 5 shows how entropy is reduced as a function of time. Each time a new feature is observed, entropy reduces. For that reason it is step-formed. The greedy approaches need more time to reduce entropy and the larger the planning horizon is, the more entropy is reduced. Furthermore when the planning horizon is small, more time is needed to observe the same number of features. Without gaze direction control entropy is not satisfactorily reduced. This results from the fact, that the gaze direction control module chooses to direct the sensor system mostly towards already observed and more certain features when the environment is known. Therefore localization error and feature position uncertainties are kept to a minimum. From the simulations it becomes clear that the proposed approach which combines gaze direction

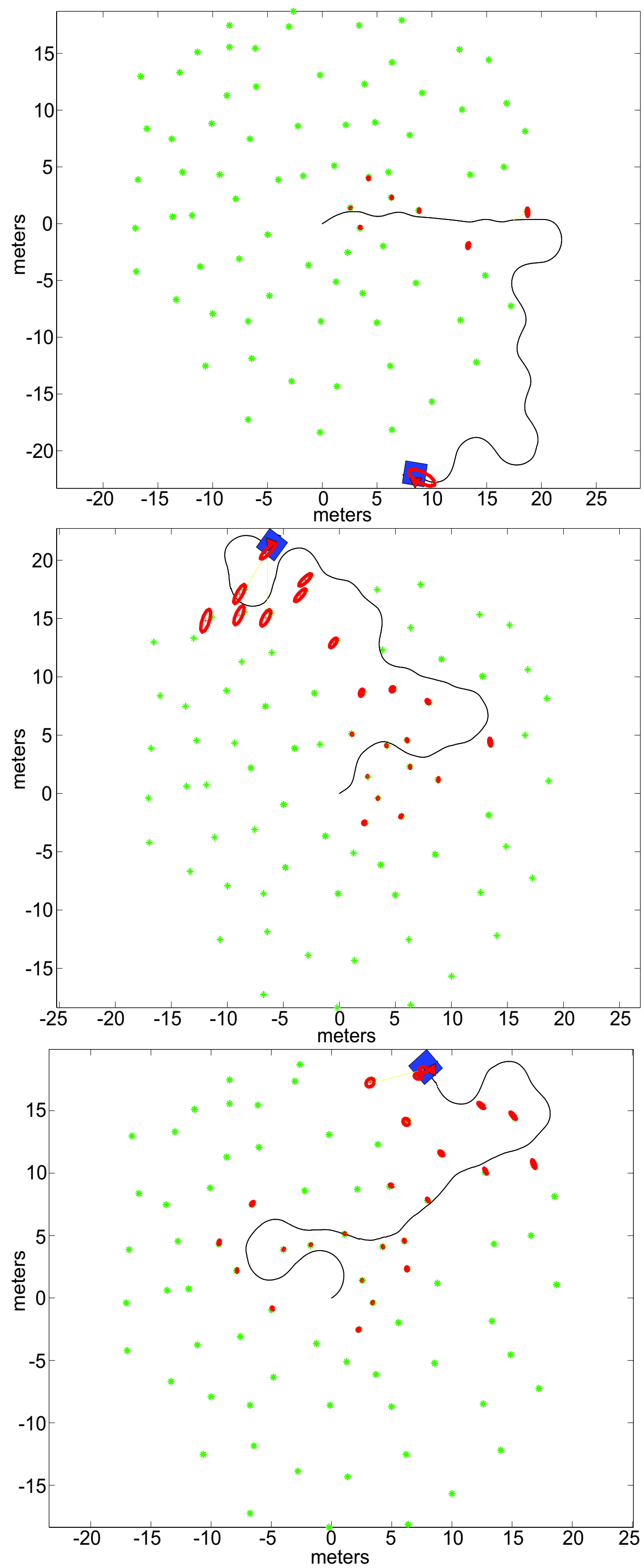

Fig. 4. Map accuracy is illustrated through the error ellipsoids of each observed feature for the final map, in the cases of (a) a one-step planning horizon without gaze direction control, (b) a one-step and (c) a three-step planning horizon. The estimated robot trajectory is illustrated by the black lines, while the red triangle on-top of the robot represents the active head and its gaze direction.

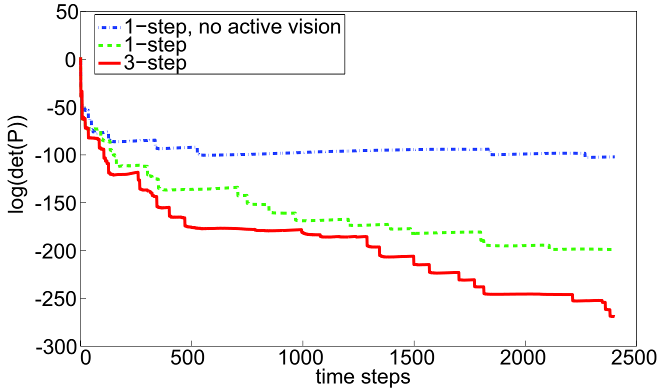

Fig. 5. $log(|\boldsymbol{P}^i_{k|k}|)$ which is a measure of entropy, as a function of time for a one-step planning horizon without gaze direction control, one-step and three-step planning horizons with gaze direction control

control and motion planning, based on information theoretic concepts, for the exploration task, gives superior results in comparison to greedy approaches and others that neglect active sensor control.

VI. CONCLUSIONS AND FUTURE WORK

A combined gaze direction control and motion planning scheme for robotic exploration was presented. It has been shown that this combination significantly improves the accuracy of the autonomously produced model of the unknown environment, even in the presence of large uncertainties in the robot and sensor models. All possible trajectories and viewing angles are evaluated over a specific time horizon and the robot controls its movement and its perception system so that the highest amount of information is collected.

Experiments with real robots will give a better idea of how well the proposed approach can deal with uncertainties which are introduced by the use of active vision and are difficult to model in simulation. For example erroneous measurements of the orientation of the vision system, errors due to the effects of motion and calibration errors. An open issue remains to find a way to adjust the planning horizon so that accurate results are produced and at the same time computational complexity is kept low.

The algorithm can be extended so that it is applicable to more complex perceptual systems that comprise several visual sensors of different resolutions. Using appropriate focal lengths and camera resolutions according to the viewing angle or even using combinations of different camera systems can dramatically improve performance. Such a multi-focal high-performance vision system has been introduced recently [16].

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REFERENCES

[1] G. Dissanayake, P. Newman, S. Clark, H Durrant-Whyte and M. Csorba, *A Solution to the Simultaneous Localization and Map Building (SLAM) Problem*. IEEE Transactions on Robotics and Automation, vol. 17, no.3, June 2001.

[2] M. Montemerlo, S. Thrun, D. Koller and B. Wegbreit, *FastSLAM: A Factored Solution to Simultaneous Localization and Mapping*. In Proceedings of the National Conference on Artificial Intelligence (AAAI), Edmonton, Canada, 2002.

[3] S. Thrun, Y. Liu, D. Koller, A.Y. Ng, Z. Ghahramani and H. Durrant-Whyte, *Simultaneous Localization and Mapping with Sparse Extended Information Filters*. International Journal of Robotics Research, vol. 23, no. 7-8, pp.693-716, 2004.

[4] F. Bourgault, A.A. Makarenko, S.B. Williams, B. Grocholsky, H. Durrant-Whyte, *Information Based Adaptive Robotic Exploration*. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Lausanne, Switzerland, Semptember 2002.

[5] H.J.S. Feder, J.J. Leonard and C.M. Smith, *Adaptive Mobile Robot Navigation and Mapping*. International Journal of Robotics and Research, vol.18, no.7, pp. 650-668, July 1999.

[6] C. Stachniss and W. Burgard, *Exploring Unknown Environments with Mobile Robots using Coverage Maps*. In Proceedings of the International Conference on Artificial Inteligence (IJCAI, Acapulco, Mexico, 2003.

[7] R. Sim, N. Roy, *Global A-Optimal Robot Exploration in SLAM*. In the Proceedings of the International Conference of Robotics and Automation (ICRA), Barcelona, Spain, April 2005.

[8] S. Huang, N.M. Kwok, G. Dissanayake, Q.P. Ha, G. Fang, *Multi-Step Look-Ahead Trajectory Planning in SLAM: Possibility and Necessity*. In the Proceedings of the International Conference of Robotics and Automation (ICRA), pp. 1103-1108, Barcelona, Spain, April 2005.

[9] M. Bryson and S. Sukkarieh, *An Information-Theoretic Approach to Autonomous Navigation and Guidance of an Uninhabited Aerial Vehicle in Unknown Environments*. In the Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Edmonton, Canada, August 2005.

[10] A.J. Davison and D.W. Murray, *Simultaneous Localization and Map-Building Using Active Vision*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no.7, pp. 865-880, July 2002.

[11] S. Se, D. Lowe, J. Little, *Mobile Robot Localization and Mapping with Uncertainty Using Scale Invariant Visual Landmarks*. International Journal of Robotics and Research, vol. 21, no. 8, pp. 735-758, August 2002.

[12] T. Vidal-Calleja, A.J. Davison, J. Andrade-Cetto and D.W. Murray, *Active Control for Single Camera SLAM*. In the Proceedings of the International Conference of Robotics and Automation (ICRA), Orlando, USA, May 2006.

[13] J.F. Seara, K.H. Strobl and G. Schmidt, *Information Management for Gaze Control in Vision Guided Biped Walking*. In the Proceedings of the IEEE/RAS International Conference on Humanoid Robots (Humanoids), Munich / Karlsruhe, Germany, October 2003.

[14] C.E. Shannon, *A mathematical theory of communication*. Bell System Technical Journal, vol. 27, pp. 379-423 and 623-656, July and October, 1948.

[15] T.M. Cover, J.A. Thomas, *Elements of Information Theory*. John Wiley & Sons, 1991.

[16] K. Kühnlenz, M. Bachmayer and M. Buss, *A Multi-Focal High-Performance Vision System*. In the Proceedings of the International Conference of Robotics and Automation (ICRA), pp. 150-155, Orlando, USA, May 2006.