

# Information-Based Gaze Direction Planning Algorithm for SLAM

Georgios Lidoris, Kolja Kühnlenz, Dirk Wollherr and Martin Buss  
Institute of Automatic Control Engineering (LSR)  
Technische Universität München,  
D-80290 München, Germany  
Email: {georgios.lidoris,koku,dw}@tum.de, m.buss@ieee.org

**Abstract**—A gaze direction planning algorithm for Simultaneous Localization and Mapping (SLAM), is presented. The objective of the algorithm is to calculate the gaze direction which minimizes estimation error over a given time horizon. This is made possible by gathering data so that the expected information gain is maximized. Existing approaches perform a greedy optimization only over the next time step and usually neglect the limited field of view of the sensors. In the proposed approach information gain is used as an objective function, in order to perform multiple step planning. This way, the novel gaze direction strategy anticipates all possible trajectories and viewing angles over a specific time horizon, performing better than other existing approaches when it comes to sensors with limitations, as most visual ones. Relative entropy of the covariance matrix provided by the extended Kalman filter (EKF) SLAM algorithm is used, as an information metric for each possible gaze direction during the multi-step planning. The aim is to create an intelligent perception module which can provide a robot with an accurate environmental model. Such a perception module is especially suited for vision-based humanoid robots.

## I. INTRODUCTION

Advances on the design, construction and motion control of humanoid robots have led to the development of several platforms, which demonstrate remarkable locomotion capabilities [1]–[3]. Therefore a significant amount of research interest has been shifted from designing new systems, to extending the cognitive capabilities of humanoid robots. This will enable them to be used in practical application fields such as entertainment, human care, industry etc.

The acquisition of an accurate environmental model based on noisy data originating from the robot sensors, is such a fundamental capability. In order to achieve that, a robot must be able to control 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 humanoid robots, this becomes equivalent to choosing the next gaze direction for the cameras in order to solve a Simultaneous Localization and Mapping (SLAM) problem.

In this paper, a gaze direction planning algorithm for SLAM is presented. The objective of the algorithm is to calculate gaze directions which minimize the estimation error over a given time horizon. This is made possible by gathering data so that the expected information gain is maximized. Existing

approaches perform a greedy optimization only over the next time step and usually neglect the limited field of view of the sensors. In the proposed approach information gain is used as an objective function, in order to perform multiple step planning. Relative entropy is used as an information metric for each possible gaze direction during the multi-step planning. The result is an intelligent perception module, which produces an accurate environmental model.

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

Simulation results are presented in Section V which show, that by controlling the active vision system of the robot according to our proposed planning approach, significantly increases SLAM accuracy in comparison with existing greedy approaches. The algorithm is shown to keep uncertainty under control in open-loop scenarios. When the loop is closed, localization error and map uncertainty are kept to a minimum, regardless of the size of the known environment. A more accurate environmental model increases robot independence, therefore allowing the robot to perform more complex autonomous tasks.

The paper is organized as follows: In the next section a brief overview of related work done in the fields of active vision, SLAM and robot exploration is presented. Next a brief overview of the EKF SLAM algorithm is given. The proposed gaze direction planning algorithm is analyzed and simulation results are presented, in order to demonstrate the performance of the proposed algorithm and compare it with greedy approaches. 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 [4]–[6], only to mention some popular ones. However this work focuses on the aspects of state estimation, belief representation and 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 are based on a greedy optimization of information gain [7]–[9]. An interesting planning approach which introduces a new measure of map quality is described in [10], but it assumes some initial state estimate of all the landmarks and it does not take into account sensors with a limited field of view. Another multi-step planning algorithm for SLAM is described in [11], but again aims at steering the robot itself and not an active sensor system. In [12] simulated results are presented which demonstrate the effect of different actions to information gain, while aerial vehicles perform SLAM based on cameras.

Very interesting work has also been done in the field of active vision. In [13] and [14] 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 [15]. Finally [16] 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.

### 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 gaze direction planning 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 [4], [8].

The state of the robot is  $\mathbf{x}_r = [x_r, y_r, \phi_r]^T$ , with  $x_r, y_r$  describing its position and  $\phi_r$  its orientation. The control input of the robot is given by  $\mathbf{u} = [u_x, u_y, u_\phi]$ . The dynamic model used is the following

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

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

The location of each environmental feature is denoted by  $\mathbf{p}_i$  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:

$$\mathbf{x}_k = [\mathbf{x}_r^T \mathbf{p}_1^T \dots \mathbf{p}_N^T]^T \quad (2)$$

The sensor observations are described by the following model.

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{d}_z \quad (3)$$

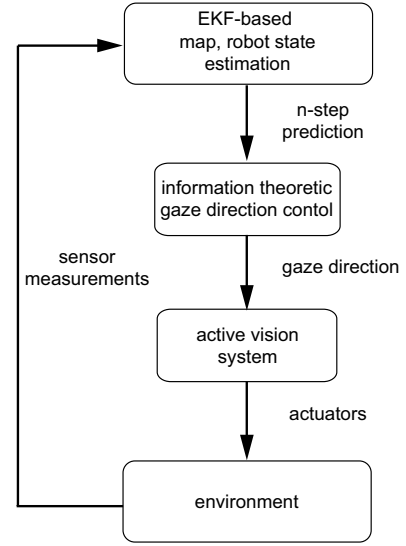


Fig. 1. Proposed gaze direction control scheme

with  $\mathbf{z}_k$  the observation vector of range and bearing measurements. The observation matrix  $\mathbf{h}$  relates the output of the sensors to the state vector  $\mathbf{x}_k$ , when observing the features and  $\mathbf{d}_z$  is the Gaussian noise vector of the observations, with covariance  $\mathbf{R}_k$ .

The Kalman filter algorithm begins with a prediction step. The knowledge of estimate  $\hat{\mathbf{x}}_{k|k}$  of the state and the state covariance matrix  $\mathbf{P}_{k|k}$  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 follows

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

$$\hat{\mathbf{z}}_{k+1|k} = \mathbf{h}(\mathbf{x}_{k|k}) \quad (5)$$

$$\mathbf{P}_{k+1|k} = \mathbf{F}_x \mathbf{P}_{k|k} \mathbf{F}_x^T + \mathbf{F}_d \mathbf{Q} \mathbf{F}_d^T \quad (6)$$

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

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

$$\mathbf{v}_{k+1} = \mathbf{z}_{k+1} - \hat{\mathbf{z}}_{k+1|k} \quad (7)$$

and the innovation covariance is

$$\mathbf{S}_{k+1} = \mathbf{H}_x \mathbf{P}_{k+1|k} \mathbf{H}_x^T + \mathbf{R}_{k+1} \quad (8)$$

with  $\mathbf{H}_x = \nabla_x \mathbf{h} |_{\hat{\mathbf{x}}_{k+1|k}}$ .

Finally the state estimate together with the state estimate covariance are updated

$$\hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \mathbf{W} \mathbf{v}_{k+1} \quad (9)$$

$$\mathbf{P}_{k+1|k+1} = \mathbf{P}_{k+1|k} - \mathbf{W} \mathbf{S}_{k+1} \mathbf{W}^T \quad (10)$$

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

#### IV. GAZE DIRECTION PLANNING

Figure 1 illustrates the proposed gaze direction control scheme. As the robot moves in its environment it builds an environmental model using the EKF SLAM algorithm that was described before, which provides it with an estimation of its state, a map and an estimation of model uncertainty. Each time new measurements come from the active vision system, the model is updated. For the gaze direction planning a multi-step prediction algorithm is used to evaluate all possible positions that can be reached by the robot over a finite time horizon, in terms of localization and map uncertainty. A finite horizon optimization is performed in order to choose the next gaze direction that minimizes localization and map uncertainties. The robot depends on noisy data gained from the visual sensors and at the same time its actions affect the quality of the collected data and its environment. All the components of the proposed approach will be examined in detail.

##### A. Measuring Information

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 information gain can be measured.

A commonly used measure of uncertainty is entropy. This concept has been introduced by Shannon in [17]. The entropy of a discrete random variable  $x$ , on a finite set  $X$  and with probability distribution function  $p(x)$  is defined as:

$$H(p(x)) = - \sum_x p(x) \log p(x) \quad (11)$$

which in the case of a multivariate Gaussian distribution with covariance  $\mathbf{P}$ , becomes  $H(x) = \frac{1}{2} \log((2\pi)^n |\mathbf{P}|)$ . Since the determinant of a matrix is a measure of 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  $\mathbf{z}$ , we will use the mutual information gain  $I[\mathbf{x}, \mathbf{z}]$ . The gain in information between any two distributions can be computed as the relative change in entropy. In our case these are the state estimates before and after making an observation, which are both multivariate Gaussians with covariances  $\mathbf{P}_{k+1|k}$  and  $\mathbf{P}_{k+1|k+1}$ . Therefore we write:

$$I[\mathbf{x}, \mathbf{z}] = H(\mathbf{x}) - H(\mathbf{x}|\mathbf{z}) = \frac{1}{2} \log |\mathbf{P}_{k+1|k}| - \frac{1}{2} \log |\mathbf{P}_{k+1|k+1}| \quad (12)$$

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

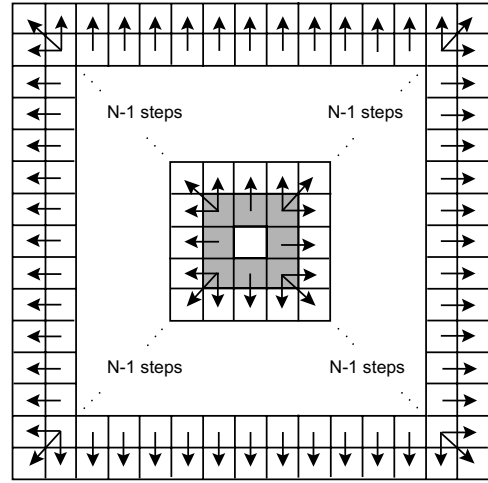


Fig. 2. Region covered while planning over a horizon of  $N$  steps. The arrows indicate which predicted states and covariances are used in each step in order to calculate the values for the next step of the planning algorithm. Highlighted grid cells show which cells are taken into account by the greedy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

##### B. Planning Algorithm

Having chosen an appropriate objective function for evaluating each environmental state, we will analyze now how this can be used to plan the gaze direction of the robot. The active perceptual system of the robot is seen as an independent module. More specifically, our intention was to create an intelligent sensing module which can provide the robot with an accurate environmental model based on very inaccurate robot models. This is of great importance since such an active sensing module can be used by many different types of robots and especially humanoids, as long as a rough robot model is available. An active stereo camera sensor system which can give range and bearing measurements, can be turned to an independent perception module which performs SLAM, if our control policy is applied.

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 multiple time steps have to be taken into account during the planning procedure.

A discretized grid environment is used, where each grid represents a position that can be reached by the robot over future time steps. Therefore the size of the grid cells depends on the physical properties of the robot. Based on this discretized environment we calculate the most informative location that can be reached over our planning horizon and then the active perceptual system is directed towards this location. While the robot moves, observations are made and they are used to update the state estimation. After the update is performed, the gaze direction is re-estimated. This way all available information is being used.

More specifically, based on an initial state estimate  $\hat{\mathbf{x}}_{0|0}$

and covariance matrix  $P_{0|0}$  we calculate all possible robot states and their covariance after  $N$  time steps and choose to observe the one that is most informative, namely the one that minimizes relative entropy, as described in the previous section. To achieve that we make use of the extended Kalman filter. 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

$$\begin{aligned}
 \hat{x}_{k|k}^i &= f(\hat{x}_{k-1|k-1}^j, \mathbf{u}_{i,k}^j) \\
 P_{k|k-1}^i &= F_{x_j} P_{k-1|k-1}^j F_{x_j}^T + F_d Q F_d^T \\
 S_k^i &= H_k^j P_{k|k-1}^i H_k^{jT} + R_k \\
 W_k^i &= P_{k|k-1}^i H_k^{jT} S_k^{(i)-1} \\
 P_{k|k}^i &= P_{k|k-1}^i - W_k^i S_k^i W_k^{iT} \quad (13)
 \end{aligned}$$

End of inner loop

End of outer loop

Choose the state estimate  $\hat{x}_{k|k}^i$  which minimizes

$$|P_{k|k}^i|$$

Calculate the new gaze direction  $G$ , according to the robot and sensor system geometrical characteristics, so that the sensor system is turned towards  $\hat{x}_{r,k|k}^i$

The planning procedure evolves in a square-like manner, as can be seen in Figure 2. Starting from the currently estimated state the first eight neighboring states and covariances are calculated. We must note here, that the first step of our planning algorithm is equivalent with the greedy approach. During the following steps the estimated state  $\hat{x}_{k-1|k-1}^j$  and covariances  $P_{k-1|k-1}^j$  of the neighboring states are used to infer the next ones  $\hat{x}_{k|k}^i$ ,  $P_{k|k}^i$  until step  $N$ . This is an important point which normally is not given much attention. By using the nearest neighbor in the estimation process, estimation error is 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  $\mathbf{u}_{i,k}^j$  and is chosen as indicated by the arrows in Figure 2. After all state covariances are estimated over the planning horizon, the most informative state is calculated. The new gaze direction  $G$  is then computed so that the active vision system is directed towards the direction of this state.  $\hat{x}_{r,k|k}^i$  is the part of the augmented state vector that contains the estimated position and orientation of the robot.

While the robot moves, observations are received which are used to update the estimated state and covariance. Each time a new state estimate is available, a correction of the planned gaze direction is made. This way we use all new information that becomes available during robot motion. It must be noted that by recalculation we don't mean replanning, simply the new estimated state of the robot is used to adjust the gaze direction, so that the sensory system is always directed to the

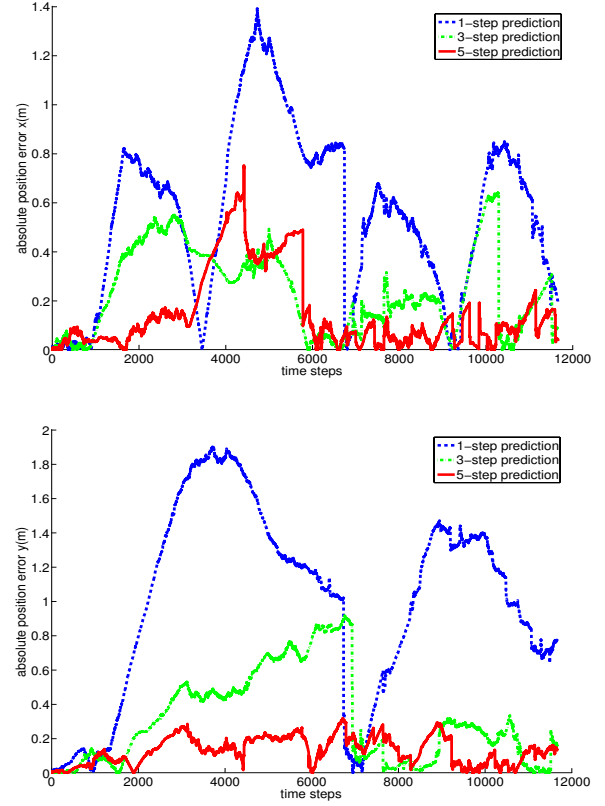


Fig. 3. Absolute position error as a function of time for one-step, three-step and five-step planning horizons

most informative region. Replanning takes place after  $N$  time steps. The planning horizon must be chosen so that the area covered during planning does not become significantly larger than the range of the sensor.

## V. SIMULATION RESULTS

The gaze direction planning algorithm has been described in the previous section theoretically. In order to evaluate its performance several simulations were conducted. Localization and map accuracy for different planning horizons are compared, in both known and unknown environments. Larger planning horizons provide better results.

### A. Simulation Description

A simulated indoor environment which contains 64 features, that are placed so that they are always at the edge of the field of view of our sensor, is used. The active simulated head which is mounted on top of the robot is assumed to have a field of view of  $60^\circ$  and a maximum viewing range of 6 meters. No previous knowledge of the environment is assumed. Feature association is considered known and all observed features are used. A harsh odometric error of 10% is chosen, since as mentioned before the algorithm must perform well 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 sensor can be moved with high angular velocities similar to the ones of the high performance vision system which is described in [18], so that saccadic movements are simulated. During simulation the robot is called to follow a given 160m long path and the active sensor system performs SLAM. The robot follows the same trajectory twice traveling a total distance of about 320m. It moves in the middle of the corridor and features are always at the limit of its sensing capacity. At first simulations were made assuming a passive sensor, directed always straight ahead of the robot. Only 9 of the 64 features were observed and the robot got lost. The necessity of gaze direction control is evident.

### B. Evaluation of Results

As the robot moves in the unknown environment, features are observed and are dynamically added to the state vector. During this phase, the ability of our algorithm to handle growing uncertainty and at the same time control the active head so that enough landmarks are observed, is tested. Afterward, the loop is closed and the robot moves around the corridors for a second time so that the performance of the algorithm in a known environment is evaluated. More specifically localization accuracy and the ability to reduce feature uncertainty in already explored environments are tested.

In Figure 3 the absolute position error is depicted, for the cases of a greedy strategy that considers only the eight neighboring states, a three step and a five step planning horizon. It is evident that localization error reduces significantly as the planning horizon grows. Up to ten-times better results are produced as the planning horizon grows. The loop closes at about time step 7000. Before the loop is closed uncertainty is kept under control, since always the most certain landmark inside the field of view is observed. After the loop is closed, localization ability seems unaffected by the distance traveled and error is kept to a minimum.

Map accuracy is illustrated in Figure 4 through the error ellipsoids for each observed feature, for the final map. It is clear that map accuracy grows as the planning horizon becomes larger. Another point that is of interest is the balance between exploration and uncertainty reduction, which is critical for gaze direction control. Most algorithms choose to observe the most certain features instead of exploring the environment to acquire new ones, resulting to small feature maps. The final map indicates that the proposed approach balances well by observing a large number of features and also building an accurate map.

Figure 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 planning approach needs more time to reduce entropy and the larger the planning horizon is, the fastest entropy is reduced. Furthermore when the planning horizon is small, more time is needed to observe the same number of features. After loop closure, at around time step 7000, only a few new features are observed so entropy does not change much. This results from the fact, that the

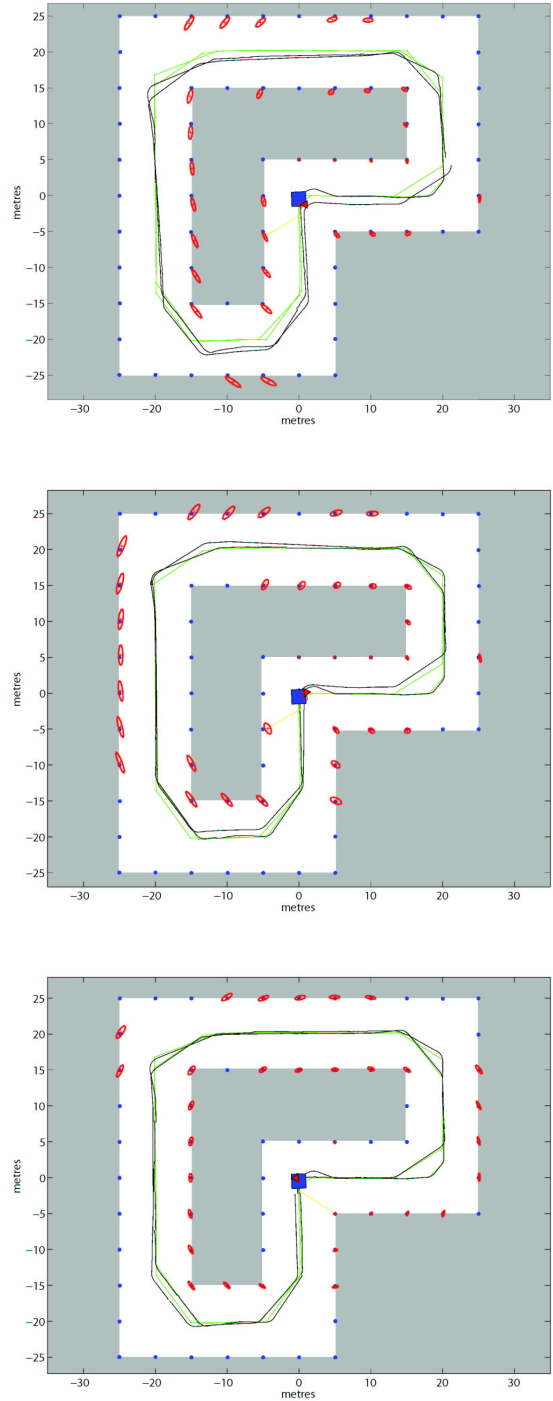


Fig. 4. Map accuracy is illustrated through the error ellipsoids of each observed feature for the final map, in the cases of (a) a one-step (greedy), (b) a three-step and (c) a five-step planning horizon. The real robot trajectory is illustrated by the green lines and the estimated one by the black lines, while the red triangle on-top of the robot represents the active head and its gaze direction.

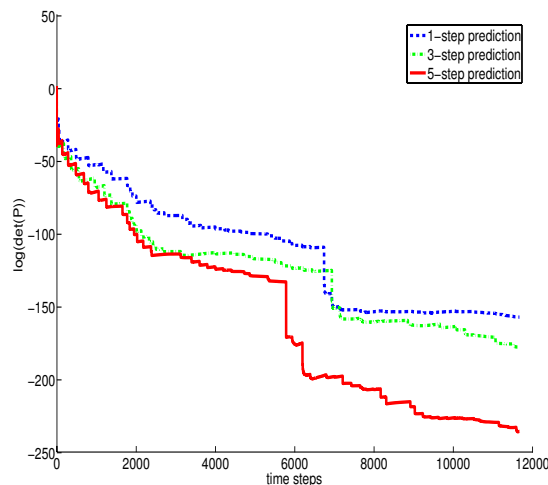


Fig. 5.  $\log(\det(\mathbf{P}_{k|k}^i))$  which is a measure of entropy, as a function of time for one-step, three-step and five-step planning horizons

planning algorithm chooses to direct the sensor system mostly towards already observed and more certain features when the environment is known. Localization error and feature position uncertainties are kept to a minimum.

## VI. CONCLUSIONS AND FUTURE WORK

A gaze direction planning algorithm for SLAM has been presented, intended for robots with active visual sensors. Through this planning procedure, all possible trajectories and viewing angles over a specific time horizon are anticipated. This enables the algorithm to perform significantly better than existing greedy approaches, which neglect the limitations of the sensors. The active perceptual system of the robot is seen in our approach, as an independent module which can provide the robot with an accurate environmental model even when it is based on very inaccurate robot models. Such a system is ideal for vision-based humanoid robots. Relative entropy is used as an information metric for each possible position and gaze direction during the multi-step planning. Simulation results are also presented which validate our approach and give a better idea of its specific properties.

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. This is an important issue, since computational complexity grows together with the planning horizon and after some point the improvement in the results becomes much smaller than the computational cost it involves.

The algorithm will be extended so that it can be applied 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 developed in our institute

[18] and it has been designed in the context of the development of new humanoid robot.

## REFERENCES

- [1] F. Pfeiffer, K. Löffler and M. Gienger, *The Concept of Jogging Johnie*. In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), Washington DC, USA, pp. 3129-3135, May 2002.
- [2] Y. Sakagami, R. Watanabe, C. Aoyama, S. Matsugana, N. Higaki and K. Fujimura, *The Intelligent ASIMO: System Overview and Integration*. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Lausanne, Switzerland, pp. 2478-2483, September 2002.
- [3] T. Ishida, Y. Kuroki, J. Yamaguchi, *Mechanical System of a Small Biped Entertainment Robot*. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Las Vegas, USA, pp. 1129-1134, October 2003.
- [4] 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.
- [5] M. Montemerlo, S. Thrun, D. Koller and B. Wegbreit, *FastSLAM: A Factored Solution to Simultaneous Localization and Mapping*. In Proceeding of the National Conference on Artificial Intelligence (AAAI), Edmonton, Canada, 2002.
- [6] 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.
- [7] 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, September 2002.
- [8] 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.
- [9] C. Stachniss and W. Burgard, *Exploring Unknown Environments with Mobile Robots using Coverage Maps*. In Proceedings of the International Conference on Artificial Intelligence (IJCAI), Acapulco, Mexico, 2003.
- [10] 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.
- [11] 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.
- [12] M. Bryson and S. Sukkarieh, *An Information-Theoretic Approach to Autonomous Navigation and Guidance of an Uninhibited Aerial Vehicle in Unknown Environments*. In the Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Edmonton, Canada, August 2005.
- [13] 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.
- [14] 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.
- [15] 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.
- [16] 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.
- [17] C.E. Shannon, *A mathematical theory of communication*. Bell System Technical Journal, vol. 27, pp. 379-423 and 623-656, July and October, 1948.
- [18] 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.