GUIDING AND LOCALISING IN REAL-TIME A MOBILE ROBOT WITH A MONOCULAR CAMERA IN NON-FLAT TERRAINS

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Abstract: In this paper we present a real-time active motion strategy for a mobile robot navigating in a non-flat terrain and its 3D constrained motion model. The aim is to control the robot with measurements from only one camera that autonomously builds a visual feature map while at the same time optimises its localisation within this map. The technique chooses the most appropriate commands maximising the expected information gain between prior states and measurements, while performing 6DOF bearing-only SLAM at real-time. The constrained 3D motion model presented here is used to infer the position of the vehicle in order to evaluate the mutual information for all possible actions at the same time. To validate the approach, not only simulations over uneven terrain have been performed, but also experimental results are shown for the technique being tested with a synchro-drive mobile robot platform with a wide-angle camera.

Keywords: Mobile robots, navigation, SLAM

1. INTRODUCTION

Actively controlling while mapping had recently acquired more attention, contrary to the purely estimation mapping techniques that had received much attention during the past 20 years. Noteworthy, and given the probabilistic nature of the Bayesian approach to the solution of the SLAM problem, entropy reduction has gained popularity as a map building strategy for driving a robot during a SLAM session in order to minimise uncertainty (Feder *et al.*, 1999; Bourgault *et al.*, 2002; Sim *et al.*, 2004).

In this paper, results are presented for actively controlling a mobile robot while performing SLAM with only one camera, with the novelty of doing so with feedback control in uneven terrains. To that, we developed a motion model constrained by the terrain and the planar vehicle caracteristics. Given the real-time particularities of the visual SLAM system we use, fast and efficient action evaluation is of utmost importance. Fortunately enough, the elements needed to validate the quality of actions with respect to entropy reduction are readily available from the SLAM priors (Davison, 2005), and, by making enough implementation adaptations, we are able to evaluate in real time the value of a limited number of actions. The technique has already been tested for an unconstrained moving camera (Vidal-Calleja *et al.*, 2006), and this paper presents the natural step forward, evaluating the technique during real-time constrained motion in 3D environments.

Action evaluation with respect to information gain has already been implemented for other SLAM systems, but little to no effort has been expended on the real-time constraint. One such approach makes use of Rao-Blackwellized particle filters (Stachniss *et al.*, 2005). When using particle filters for exploration, only a very limited number of actions can be evaluated due to the complexity in computing the expected information gain. The main bottleneck is the generation of the expected measurements each action sequence would produce, which is generated by a ray-casting operation in the map of each particle. In contrast, measurement predictions in a feature-based EKF implementation can be computed much faster, having only one map posterior per action to evaluate, instead of the many a particle filter requires. Moreover, in (Stachniss *et al.*, 2005) the cost of choosing a given action is substracted from the expected information gain with a user selected weighting factor. In this work, we show the cost of performing a given action is inherently taken into account when evaluating the entropy for a set of possible priors.

Sim has also addressed decision making for the robot exploration problem, as an optimisation problem for a restricted hand-crafted set of exploratory policies (Sim *et al.*, 2004). Other approaches include, for example, a multirobot stereo-vision occupancy grid-based SLAM system (Rocha *et al.*, 2005), with best single-step look ahead chosen on the basis of overall map entropy reduction. In such a discrete representation of the map posterior, overall map entropy is computed as the sum of individual entropies for each grid cell. Bryson *et al.* on the other hand, present simulated results of the effect different vehicle actions have with respect to the entropic mutual information gain (Bryson and Sukkarieh, 2005). The analysis is performed for a 6DOF aerial vehicle equipped with one camera and an inertial sensor, for which landmark range, azimuth, and elevation readings are simulated, and data association is known.

We have opted for a strategy that chooses those actions that maximise the mutual information between states and measurements. The expected information gain is evaluated propagating a particular action using the constrained motion model proposed here, with the advantage this model considers the non-holonomic constraints of the vehicle and the slope of the terrain. Notice that maximising an information criterion might result in uncertain actions being chosen, since their reduction of uncertainty once a measurement has taken place would be larger. Other reported approaches maximise present to future posterior entropy differences instead. With our chosen strategy overall entropy decay may happen at a lower pace, at the expense of actually choosing exploratory actions instead of homeostatic ones. Actions are compared at the same instant but evaluated at different time, that is the reason of using mutual information, instead of entropy, together with the nonlinearity of the constrained motion model.

The rest of the paper is distributed as follows. Section 2 presents a brief overview of the vision-based bearing only SLAM system we use. Section 3 is devoted to a discussion from first principles on the value of expected measurements in reducing overall state entropy. This gives rise to the actual action selection policy used, which is described in detail in Section 4. Section 5 presents an evaluation of our exploration strategy for a 3D simulated environment; and Section 6 contains actual experimental results. Finally, some concluding remarks are given in Section 7.

2. EKF 6DOF BEARING-ONLY SLAM

2.1 Unconstrained Camera Motion

Considering initially that our sensor is a camera, and that it is free to move in any direction in $\mathbb{R}^3 \times SO(3)$, we adopt the same smooth unconstrained constant velocity motion model as in (Vidal-Calleja *et al.*, 2006),

$$\mathbf{x}_{v,k+1|k} = \begin{bmatrix} \mathbf{p}_{k+1|k} \\ \mathbf{q}_{k+1|k} \\ \mathbf{v}_{k+1|k} \\ \boldsymbol{\omega}_{k+1|k} \end{bmatrix} = \begin{bmatrix} \mathbf{p}_{k|k} + (\mathbf{v}_{k|k} + \mathbf{a}_k \Delta t)\Delta t \\ \boldsymbol{\mathcal{Q}}\mathbf{q}_{k|k} \\ \mathbf{v}_{k|k} + \mathbf{a}_k \Delta t \\ \boldsymbol{\omega}_{k|k} + \boldsymbol{\alpha}_k \Delta t \end{bmatrix} . \tag{1}$$

Suffice to say that $\mathbf{p} = [x, y, z]^\top$ and $\mathbf{q} = [q_0, q_1, q_2, q_3]^\top$ denote the camera pose (three states for position and four for orientation using a unit norm quaternion representation), and $\mathbf{v} = [v_x, v_y, v_z]^\top$ and $\boldsymbol{\omega} = [\omega_x, \omega_y, \omega_z]^\top$ denote the linear and angular velocities, respectively, corrupted by zero mean normally distributed linear and angular accelerations $\mathbf{a} = [a_x, a_y, a_z]^\top$, and $\boldsymbol{\alpha} = [\alpha_x, \alpha_y, \alpha_z]^\top$. The quaternion transition matrix is

$$\boldsymbol{\mathcal{Q}} = \cos\left(\frac{\Delta t \|\boldsymbol{\Omega}\|}{2}\right)\mathbf{I} + \frac{2}{\|\boldsymbol{\Omega}\|}\sin\left(\frac{\Delta t \|\boldsymbol{\Omega}\|}{2}\right)\boldsymbol{\Omega}_\times \tag{2}$$

with $\boldsymbol{\Omega} = [0, \omega_x, \omega_y, \omega_z]^\top$ the angular velocity vector expressed in quaternion form, and $\boldsymbol{\Omega}_\times$ its skew-symmetric matrix representation.

2.2 Constrained Camera Motion

It is assumed, however, that such camera is attached to a mobile robot navigating in a 3D terrain. The mobile robot is controlled by linear and angular velocities $\mathbf{u} = [v_r, \omega_r]^\top$ which are tangent to the terrain surface. In simulating the robot motion taking into account surface contact at all times, we can substitute the previous motion prediction model with a constrained model for the continuous transition of the optic centre of the camera

$$\begin{bmatrix} \mathbf{p}_{k+1|k} \\ \boldsymbol{\theta}_{k+1|k} \end{bmatrix} = \begin{bmatrix} \mathbf{p}_{k|k} \\ \boldsymbol{\theta}_{k|k} \end{bmatrix} + \boldsymbol{\Gamma}\mathbf{u}_k \Delta t, \tag{3}$$

where

$$\boldsymbol{\Gamma} = \begin{bmatrix} -\sin\phi\sin\psi - \cos\phi\cos\psi\sin\theta & -l\cos\psi\cos\theta\cos\phi \\ \cos\phi\sin\psi - \sin\phi\cos\psi\sin\theta & -l\cos\psi\cos\theta\sin\phi \\ \cos\psi\cos\theta & -l\cos\psi\sin\theta \\ 0 & \sin\psi\tan\theta \\ 0 & \cos\psi \\ 0 & \frac{\sin\psi}{\cos\theta} \end{bmatrix},$$

$\boldsymbol{\theta} = [\psi, \theta, \phi]^\top$ is a *yaw, pitch, roll* representation of $\mathbf{q}$, and l is the distance between the axle centre of the mobile robot and the camera optic centre.

2.3 Measurement Model

Our 6DOF Single Camera SLAM system extracts salient point features from images, building a map of their 3D coordinates. Image projection priors are estimated with a full perspective wide angle camera

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} u_0 - u_c/\sqrt{d} \\ v_0 - v_c/\sqrt{d} \end{bmatrix} \tag{4}$$

where the position of a 3D map point is first transformed into the camera frame $\mathbf{y}_i^c = \boldsymbol{\mathcal{R}}(\mathbf{y}_i - \mathbf{p})$, with $\boldsymbol{\mathcal{R}}$ the rotation matrix equivalent of $\mathbf{q}$, and $u_c = fk_u x^c/z^c$, $v_c = fk_v y^c/z^c$. The radial distortion term is $d = 1 + K_d(u_c^2 + v_c^2)$, and the intrinsic calibration of the camera is known — focal distance f, principal point (u_0, v_0), pixel densities k_u and k_v, and radial distortion parameter K_d.

These priors are then compared against actual measurements using a nearest neighbour test within a 3σ elliptical search region inside the innovation covariance $\mathbf{S}_i$ for each image estimate (Vidal-Calleja *et al.*, 2006). New features are initialised using the approach presented in (Davison *et al.*, 2003).

3. INFORMATION GAIN

The exploration strategy proposed in this paper is aimed specifically at maximising the mutual information between the state and consequent measurement priors, both resulting from an action in the form of a motion command. Different commands give rise to better or worse priors (in an entropic sense), and we want to select, from a limited test set, the one that produces the most expected reduction in entropy for the entire state, once the consequent measurement has taken place.

The mutual information for these two continuous probability density functions is

$$I(X;Z) = E\left[\log \frac{p(\mathbf{x}|\mathbf{z})}{p(\mathbf{x})}\right] . \tag{5}$$

For our Gaussian Multivariate case, the prior distribution is simply $p(\mathbf{x}) = N(\mathbf{x}_{k+1|k}, \mathbf{P}_{k+1|k})$, whereas, the conditional is given by the Kalman posterior $p(\mathbf{x}|\mathbf{z}) = N(\mathbf{x}_{k+1|k+1}, \mathbf{P}_{k+1|k+1})$ with the updates

$$\mathbf{x}_{k+1|k+1} = \mathbf{x}_{k+1|k} + \mathbf{P}_{k+1|k}\mathbf{H}^\top\mathbf{S}^{-1}(\mathbf{z}_{k+1} - \mathbf{z}_{k+1|k}) \tag{6}$$

$$\mathbf{P}_{k+1|k+1} = \mathbf{P}_{k+1|k} - \mathbf{P}_{k+1|k}\mathbf{H}^\top\mathbf{S}^{-1}\mathbf{H}\mathbf{P}_{k+1|k}^\top \tag{7}$$

Taking the expectation in Eq. 5, the Mutual Information between our state and measurement priors evaluates to the difference between prior and posterior state entropies

$$I(X;Z) = \frac{1}{2}(\log|\mathbf{P}_{k+1|k}| - \log|\mathbf{P}_{k+1|k+1}|) . \tag{8}$$

In other words, maximising the mutual information between the state and measurement priors we end up choosing the motion command that most reduces the uncertainty in the state due to the knowledge of the consequent measurement as a result of a particular action.

4. CONTROL STRATEGY

The control scheme is based on computing the instant robot accelerations that maximise mutual state and measurement information gain. The chosen command is then integrated to produce the input velocity that is sent to the robot. Given the real-time limitations of our system, only a limited number of actions can be evaluated at each step. These are shown in the discrete set from Table 1.

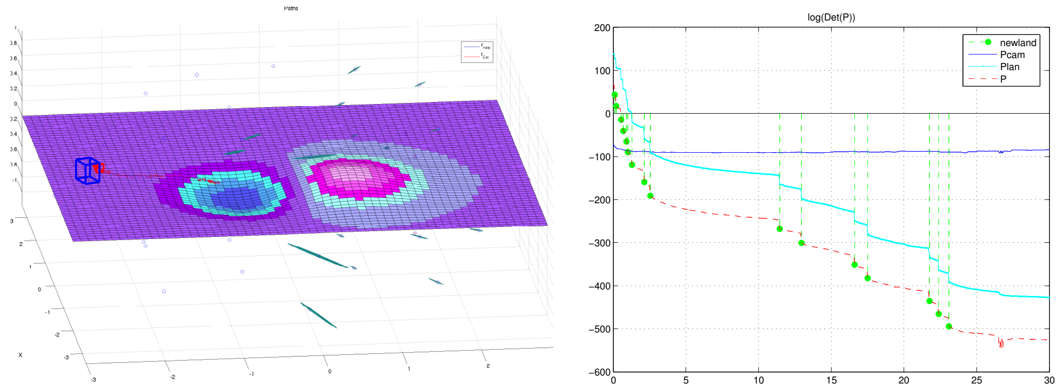
Table 1. Action Set

Action	Linear Acceleration	Angular Acceleration
0	0	0
1	0	$-\dot{\omega}_r$
2	0	$\dot{\omega}_r$
3	$-\dot{v}_r$	0
4	$\dot{v}_r$	0
5	$-\dot{v}_r$	$-\dot{\omega}_r$
6	$\dot{v}_r$	$\dot{\omega}_r$

To compare the gain of information each of these actions would produce, the constrained motion model from Eq. 3 is used to predict the expected prior mean $\mathbf{x}_{k+1|k}$ for each instant acceleration in the set, propagating the covariances by computing the corresponding Jacobians. Map features priors are also used to simulate the expected observations using the camera measurement model and the state prior. The posterior covariance is then computed taking into account only known features inside the camera field of view.

At each time step we compute, in turn, the mutual information for one action in the set, using the prior and posterior covariance matrices. That is, for every linear and angular instant acceleration combination. Every 15th cycle, once all possible actions have been evaluated for a lapse of at least 8 cycles, the action that maximises the mutual information is chosen, and a new velocity input is sent to the system.

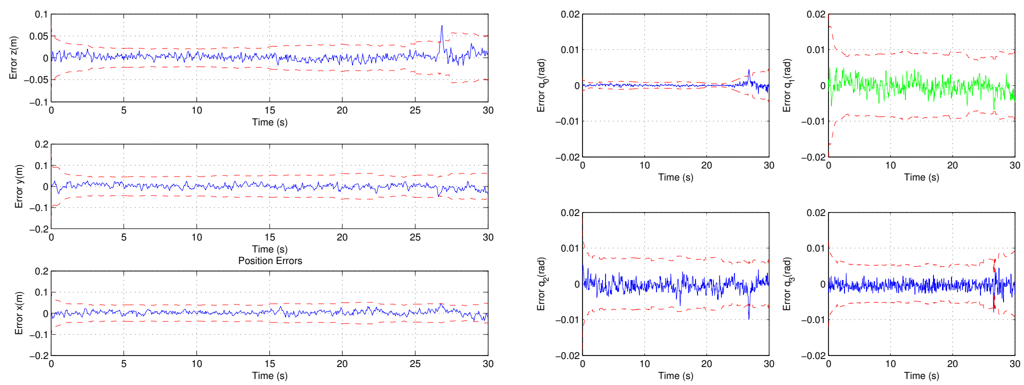
It is assumed that a fixed number of expected features will be found within a 3D unexplored room. During the action selection process, the unknown features are taken into account only



(a) Simulated robot trajectory

(b) Camera, map, and total entropies

Figure 1. Simulation of a mobile robot actively exploring a room. The mutual information maximisation strategy produces a nearly linear motion tangent to the surface. The vehicle starts at the shown terrain depression and proceeds backwards slightly rotating to increase map coverage. ($\mathbf{r}_{\texttt{Real}}$ and $\mathbf{r}_{\texttt{Est}}$ are the real and estimated vehicle trajectories, the label **`newland`** and the green dots and dotted vertical lines represent the value of entropy at the instant when new landmarks are initialised. **`Pcam`**, **`Plan`**, and **`P`** indicate the robot, map, and overall entropies.)



(a) Position error

(b) Orientation error

Figure 2. Estimation errors for camera position and orientation and their corresponding 2σ variance bounds. Position errors are plotted as x, y, and z distances to the real camera location in meters, and orientation errors are plotted as quaternions.

in the covariance matrix initialised with large uncertainty.

5. SIMULATIONS

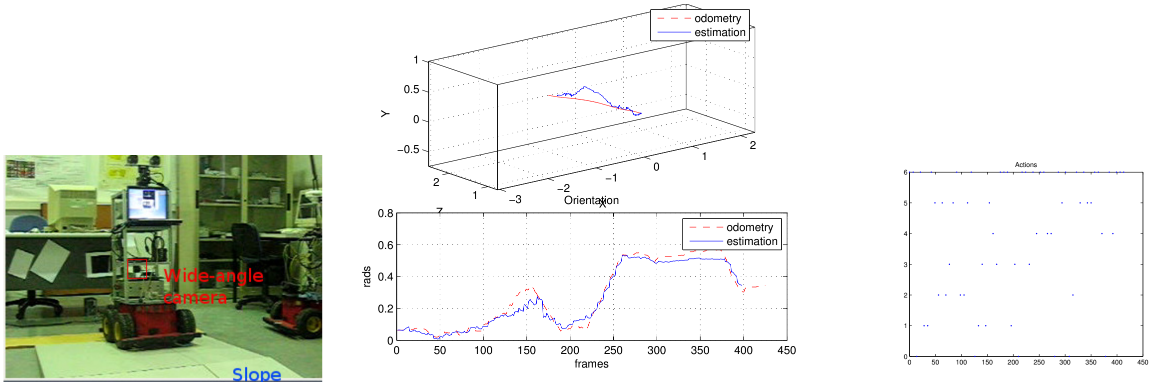
Extensive simulations have been performed using the constrained motion model for the mobile robot from Eq. 3, navigating in uneven 3D terrain, and using a full perspective wide angle camera model as sensing device.

The aim is to choose impulsive acceleration commands for the mobile robot in order to explore the whole room while trying to reduce most the uncertainty. Accelerations are applied only every 15th step, and in between action decision, null acceleration is set, i.e. constant velocity behaviour is chosen until a new action is decided.

The control action is chosen from the discrete set of instant linear and angular accelerations shown in the Table 1. The values for $\dot{v}_r$ and $\dot{w}_r$ that produced the results shown in this section are $0.5m/s^2$ and $0.3rad/s^2$ respectively. The simulated environment shown contains 25 unknown features and 6 known features uniformly distributed in the room. Our simulated wheeled mobile robot is navigating over a 3D sinusoidal surface.

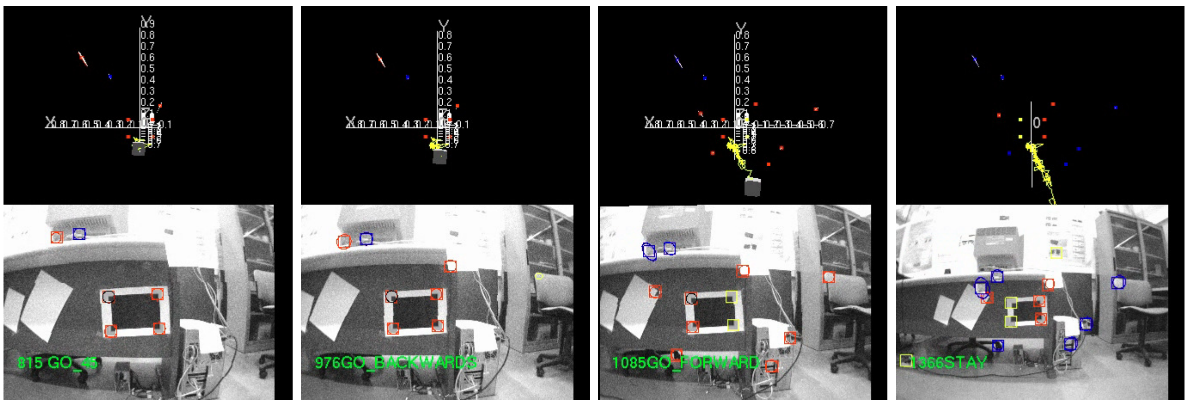
Figure 1(a) shows the trajectory followed by the vehicle and the initialised features with their uncertainty plotted as 2σ level hyperellipsoids. The expected covariance matrix is extended with the unknown feature uncertainties with diagonal values of $5m^2$ each to avoid homeostasis. Entropy reduction is computed using the extended covariance. The instant at which new features are added to the state are shown in Figure 1(b). Moreover, state estimation errors for the camera pose are shown in Figure 2. Notice how when the terrain abruptly changes, the estimated velocities become underestimated in the direction the terrain changed.

The selected actions reduce the camera pose and velocity uncertainty first, tracking features with low uncertainty. After that, the variance for unvisited features with large uncertainty is reduced



(a) Mobile robot (b) 3D paths (c) Actions followed

Figure 3. Setup, trajectories and actions during the experiment.



(a) frame 240 (b) frame 290 (c) frame 350 (d) frame 400

Figure 4. Snapshots of the Graphical User Interface during autonoumous exploration.

as new features are added. Interestingly enough, the system autonomously explores by repeatedly choosing a negative linear acceleration. The effect is to augment the camera field of view with the consequent inclusion of new feature in the model, but still maintaining known features in sight, thus keeping the vehicle well localised at all times. In contrast to our previous experiments reported with a free-moving hand-held camera (Vidal-Calleja *et al.*, 2006), it is more difficult in this constrained motion setting to actively perform short loop closure orthogonal to the field of view. The reason being that the robot cannot achieve saccadic motions in the way a free-moving camera can.

At this point we can argue how the same tracking (unconstrained constant velocity 6DOF motion model) and action selection strategies (maximising the mutual information between states and measurements) is capable of choosing different exploratory manouvers depending on the characteristics of the platform: short loop closing for a 6DOF free-moving camera, and backwards linear motion increasing the field of view for a mobile robot.

6. EXPERIMENTS

Our main concern was to test the strategy during real-time vision-based SLAM execution. This Section is devoted to a discussion on such results. The experiments were conducted on a Pioneer 2AT mobile platform with a wide-angle camera rigidly attached to the robot body, and for which an updated version of the single camera SLAM system reported in (Davison *et al.*, 2004) was setup.

Within a room, the robot starts approximately at rest with some known object in view to act as a starting point and provide a metric scale. The robot moves, translating and rotating constrained by the 3D terrain, such that various parts of the unknown environment come into view. The aim is to estimate and control the 6DOF camera pose continuously, promptly and reliably during arbitrarily long periods of movement. This will involve accurately mapping (estimating the locations of) a sparse set of features in the environment.

The whole process is running at 15fps. Since our mutual information measure requires evaluating the determinant of the full covariance matrix (enlarged with the unvisited features) at each iteration, single motion predictions are evaluated one frame at a time. It is only every 15th frame in the sequence that all mutual information measures are compared, and the best action is sent to the mobile robot. For the experiments, the acceleration magnitudes were set to $\dot{v}_r = 0.1 m/s^2$ and $\dot{\omega}_r = 5 deg/s^2$. When computing posteriors, these are all predicted for the duration that would take them to the end of the 15th frame, each action in turn being evaluated for a slightly shorter period of time. The motivation is that we want to be able to test actions in the basis of their effect at the very same point in time (at the end of the 15th frame). In order to evade any bias related to the time spent in evaluating the effect of actions, these are randomly ordered at each iteration. A feedback control is set to guarantee the desired action is accomplished until the new action is received.

As with the simulated setting, the robot navigates in uneven terrain as shown in Figures 3(a) and 3(b). In the plot, the estimated path (blue continuous line) is shown in 3D, as opposed to the vehicle odometry which is restricted to the $Z - X$ plane. The orientation angle from Figure 3(c) indicates the vehicle orientation with respect to the world axis Y (orthogonal to the white sheet of paper placed in front of the robot, which serves as global reference consistent to the world $Z - X$ plane). Estimation in this case is similar to the measure provided by the encoders.

As in the simulated case, our mutual information-based action selection strategy for this constrained motion case autonomously explores the room driving the vehicle back and forth, but mostly backwards, enlarging the field of view by pulling away from the initial view.

Figure 3(c) gives account of the actions sent to the robot, and shows as most frequent actions iterations between positive and negative linear acceleration. The feature map and camera pose are updated and displayed in real-time in the graphical user interface. Figure 4 shows a sequence of frames from the same experiment, that show the robot driving away from the start known features.

7. CONCLUSION

This paper has presented an autonomous exploration strategy for a wheeled mobile robot equipped with a single wide angle camera and navigating in uneven terrains. The approach is based in choosing the action that maximises the information gain between state and measurement priors evaluated in the 3D constrainted motion model presented here. Simulation and experimental results consistently show a behaviour in which the robot pulls back from an initial configuration, by having the camera search for more features whilst reducing its own pose uncertainty.

The reported camera trajectories are simple because firstly the robot is commanded by acceleration impulses that tend to drive the robot through smooth velocity changes, and secondly the real-time constraints of the implementation allow only for the evaluation of a very limited set of possible actions at each step. The computational complexity in computing entropy does not permit large maps, in that case submapping will be a good solution.

With only one camera it is possible to localise the mobile robot in a 3D environment, in addition our approach produces the velocity control command necessary to reduce more the uncertainty of the camera pose and features position taking into account the constraints of the vehicle and the ground floor.

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