PG2P: A perception-guided path planning approach for long range autonomous navigation in unkown natural environments

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***Abstract*— This paper presents a new hybrid path planning approach for autonomous robots navigating in natural unknown environments. The main purpose is to consider perception planning and path planning in a single unified process, so that the most relevant perception can be performed considering the current goal of the robot. We consider this approach as a way to fill the gap between navigation tasks and exploration tasks. In a first part, we introduce the models and notions used in this approach. We then give some algorithmic details, and finally present results in simulation.**

I. Introduction

Long range autonomous navigation in unknown (or partially known) environments recently became a main focus for many contributions. In order to increase autonomy, numerous problems have to be tackled simultaneously such as localization, trajectory planning or decision making. This paper especially deals with path planning in the context of a *navigation task*, *i.e.* where the mission is to reach a given distant goal. In unknown or partially known environments, path planners usually rely on a dynamic path finding algorithm. Among the most popular, Stentz's D* [10] and further improvements [11], [6] provide with a powerful way to plan and re-plan paths in a dynamically updated representation of the environment. This approach has been successfully integrated, for instance, as a global path planning paradigm, in [9].

However, these approaches for path planning focus on the speed and the quality of the path search into a traversability graph: they do not have any concern with the opportunity to control the perception actions, that may drastically, from our point of view, improve the quality and the relevance of the perceived data that will be used to update the representation's model of the environment.

Path planning and perception planning should be intrinsically dependant [1], [5], in such a way that each of these planning may expect the more benefits from the other : the more promising perception leading to the best possible path (considering the current knowledge). This paper presents such a path planning paradigm, called perception-guided path planning (PG2P).

Role of PG2P during navigation : Whatever the considered rover, natural environments exhibit a variety of situations that call for various motion modes. We favor an approach in which the rover adapts its motion mode to the kind of terrain it has to traverse, which satisfies a general "economy of means" principle, and tends to achieve an efficient behavior [3]. Basically, two kinds of motion modes can be distinguished:

- **Reflex** modes: when the environment is "easy", *i.e.* rather flat and lightly cluttered, the robot can efficiently move just on a basis of a close goal to reach and information provided by "obstacle detector" sensors. In essentially flat environments, information returned by the observation of a laser stripe might be sufficient; when the environment is known to contain obstacles, a broader perception (as provided by stereovision) is required in order to safely execute avoiding maneuvers.
- **Planned** modes: reflex modes become inefficient when applied in more complex environments, in which the robot can be trapped in dead-ends for instance. In such cases, trajectory planners reasoning on a model of the environment are required. Depending on the difficulty of the area to cross, a 2D planner can find out ways between obstacles using a description that exhibits traversable and non-traversable areas, or a 3D planner that checks stability and collision constraints thanks to a fine 3D model of the environment [2].

The existence of different motion modes enables to choose a well adapted and efficient behavior depending on the terrain, but it complicates the system, that has to deal with several different terrain representations and motion planning processes. It especially requires the ability to select *(i)* the adequate motion mode to apply, *(ii)* the sub-goal to reach and *(iii)* the next perception task to achieve. This is the role of perception-guided navigation planner.

The next section introduces the notions and models required as a framework for our approach.

II. Models: rover, terrain and perception

A. Rover's expected capabilities

We suppose that the rover is endowed with n motion generation capabilities, adapted to given terrain traversability classes. A cost is associated to each motion mode, encompassing the time required by the dedicated environment model to build (*e.g.* a digital elevation model for rough areas), the time necessary to generate motion commands, and the maximum reachable speed for the considered motion mode.

B. Terrain and perception model

Each of the different motion modes requires a particular terrain representation, but the navigation planner also requires a specific terrain representation in term of traversability classes: *the region map*.

Each time 3D data is acquired, the region map is built thanks to a fast classification process that produces a probabilistic description of the perceived areas in term of *terrain classes*, akin to a multi-valuated occupancy grid representation. It relies on a specific discretisation (figure 1) of the perceived area, that defines "cells" on which different relevant characteristics (attributes) are determined. A non-parametric Bayesian classification procedure is used to label each cell: a learning phase based on prototypes classified by a human lead to the determination of probability density functions, then the classical Bayesian approach is applied, which provides an estimate of the probability for each cell to correspond to one of the defined terrain classes (*e.g.* {*Unknown, Flat, Rough, Obstacle*}).

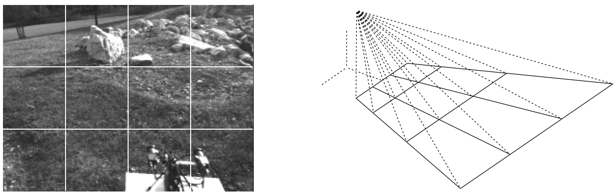

Fig. 1. Discretisation of a 3D stereo image: regular Cartesian discretisation in the sensor frame (left - only the correlated pixels are shown), and its projection on the ground (right - the actual discretisation is much finer)

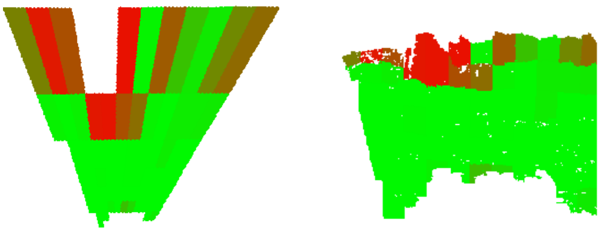

Fig. 2. Binary classification of the stereo image of figure 1: perceived area (left) and reprojection in the sensor frame (right). Colors represent the probabilities in a green/red ↔ flat/obstacle scale

The partial probabilities of a cell to belong to a terrain class allow to perform a fusion procedure of several classified images. The fusion procedure is performed using a bitmap. For the purpose of navigation planning, the bitmap model is structured into a global region map of fixed square areas that define a connection graph, whose nodes are on their borders, and whose arcs correspond to a region crossing. To each region is associated the terrain classes partial probabilities label, the confidence on this labeling and elevation informations. Figure 3 is an example of a binary region map produced during navigation. The rest of the paper deals only with two-classes {*traversable, obstacle*}) region maps, only considering actually one motion mode, but all our developments are applicable to region maps with any number of terrain classes.

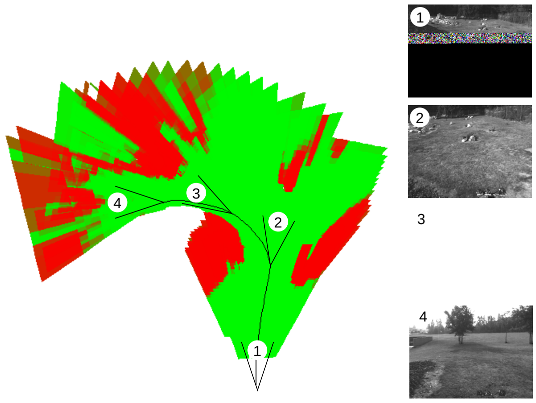

Fig. 3. A qualitative terrain model integrating 50 stereo pairs, acquired along a trajectory (same colors code as in figure 2)

C. Perception model: entropy Vs confidence of perception

Deciding where to perceive is usually considered as an exploration-related purpose. This problem requires to be able to compare several opportunities of perception, given a particular configuration of the rover in the environment.

Several contributions related to this class of problems deal with the notion of entropy [8], as a mean to assess the quantity of information associated to a probability distribution on the terrain classes (flat, obstacle). Considering up to three classes, Shannon's entropy is known as a relevant way to assess this quantity of information:

where is the class out of n. Hence Shannon's entropy gives rise to the following properties:

n $\frac{}{n}$

The higher the entropy, the weaker the information. Using this mean provides with an interesting policy to select the next place where to perform a perception action. This is often used as a classical greedy (and sometimes quite efficient) approach to exploration [7]. However, the notion of entropy is not sufficient in the context of planning perception in navigation-related problems: if one can predict the evolution of the entropy with the sensor model when evaluating the effect of a perception action, it will not help to assess how the path cost is modified on the perceived aera.

Hence we decided to introduce a concept of *Confidence Of Perception* (COP) , depending only on a priori knowledge regarding the perception device's behavior. For our perception model, this confidence is proportionnal to the resolution of the perceived data, therefore this confidence can be stated as a function of the perception distance: COP n . The COP is high when a perception has been performed very close to the considered location, and inversely COP = 0 when the considered location has still never been perceived. As far as this concept does not depend on the probability distribution over the terrain classes, we may expect to be able to foresee how performing a perception action at a given location will affect the COP onto this location.

The idea is not to substitute this COP to the notion of entropy: comparing opportunities of perception directly in term of COP evolution would sound like a weak criterion. However, an interesting way to deal with this concept is to consider its effect on the traversability costs: this provides a way to compare the effects of performing perception actions regarding the paths costs.

This is the foundation of our perception-guided navigation paradigm, described in the next section.

III. The PG2P paradigm

A. Planning paths in unknown environments

1) D like algorithms:* Real time path re-planning is a major requirement for an efficient navigation in an unknown environment. The efficiency of D*-like algorithms results from the assumption that, for each iteration, only small areas (compared to the whole map size) of the terrain map are affected by traversability cost modifications. This is obviously the case when the map is updated thanks to local perception information, as it usually happens when a rover navigates inside an unknown environment, using local-range sensors to perform perception. Hence we chose to use a classical D* in our approach, to benefit from this efficiency in term of computation time.

2) Traversability cost function: A key point in our approach is the notion of COP introduced earlier: it is used to define a new traversability cost function depending both on the probability distribution over the terrain classes and on the COP:

As a result, a high COP for a given cell will give rise to a reinforcement of the "behavior" of the traversability cost's function, as shown on figure 4. Moreover, as noticed in section II-C, the COP is predictable: whatever perception action is planned, we have the opportunity to assess the a priori effects of the perception in terms of COP evolution. Hence we may use this property to simulate perceptions performances while observing the path cost evolution when updating the COP.

Fig. 4. Incidence of the COP on the traversability cost

The influence of the COP on the traversability cost drastically modifies the perception planning behavior. This is one of the main point of control in our approach: if COP's influence is set to a low level, then the navigation behavior sounds like a classical D*-guided navigation. On the other hand, if COP's influence is set to a high level, then the rover tends to lose its focus (the goal point) and hence behaves like greedily exploring its environment.

B. Decision theoretic and perception planning

1) Perception action: Deciding whether a given zone is worth to be perceived or not, can be tackled by applying a decision theoretic technique [4]. In our approach, we suggest to design two functions of utility for each terrain class: the utility to perceive a given node, and the utility not to perceive it regarding its class.

Fig. 5. Utility to perceive flat terrain (left), and not to perceive flat terrain (right)

Fig. 6. Utility to perceive obstacle terrain (left), and not to perceive obstacle terrain (right)

We designed utility functions as shown in the following equations, which stands for the terrain class:

where coefficients , , and are modulated in order to design the expected utility's values.

The computation of the difference, for a given node, provides us with a serious clue about the relevance to perceive this node, regarding a given class. Each utility function takes into account the following parameters:

- Current probability over the considered terrain class,
- Current COP, as defined in section II-C,
- Adjustment parameters, that will give rise to navigation strategies adjustment opportunities.

Fig. 7. Total difference of utility as a function of and COP

With two terrain classes (flat/obstacle) and with the utility functions of figures 5 and 6, the total difference of utility (TDU) function illustrated in figure 7 is computed with balancing the difference of utility for each class with the respective probability to belong to the class:

where is the utility function to perceive, and the utility function not to perceive.

The greater the total difference of utility (TDU), the more interesting the perception. A node whose TDU is greater than 0 will have an utility greater if perceived than if not. This provides us with a way to choose whether to perceive a given node or not.

Figure 7 shows that there is a maximum of tolerance to COP when the probability of obstacles is around 0.5: with two classes, this probability represents an uncertainty about the kind of terrain (flat or obstacle). Therefore when a “0.5 probability of obstacle” node is assessed, its COP may be high, while staying interesting to perceive. As a result, a node that has been perceived a first time but has not been classified discriminately (i.e. with a high entropy) will remain interesting to perceive, as long as its COP will remain low enough so that the TDU . In the algorithm (described in section III-C), this TDU will be computed onto all the nodes covered by a given perception: considering only the nodes whose TDU , we get an “a priori” overall score of interest for this perception action. This will be used as a basic scheme for the selection of the most interesting perception action while performing our path planning paradigm.

2) Access frontier: The access frontier, in a given configuration of the traversability map, will be defined as the set of nodes, in the vicinity of the robot, belonging to an “accessible zone”, and having at least one neighbor that is not. This set of nodes represent the frontier from where perception actions may be performed in a secured and efficient way (similarly to [12]): in the same way the decision theoretic provides us with a scheme to decide whether a given node is worth to be perceived or not, we also suggest to apply this scheme to assess whether a given node should be considered as belonging to the accessible zone or not. This zone will contain nodes whose COP and probability distribution over the classes are coherent with the rover capabilities and physical requirements. Therefore the corresponding decision function will behave rather like the opposite of the decision function describing the decision for the perception interest: an accessible zone is usually not worth to be perceived, since a certain degree of knowledge will already be assumed.

Fig. 8. Total difference of utility for the accessibility

The pairs of utility functions corresponding to the different terrain classes are computed, and finally, the total difference of utility (figure 8) let us decide whether a given node should belong or not to the ”accessible zone”. Hence each node of the access frontier will be assessed as a possible base point for the next perception to perform. It should be noticed that the parametrization of this TDU function directly affects the whole reachability within our method : a low tolerance for the accessibility may forbid the discovery of any path toward the goal.

C. Algorithm detail

This part focusses on the implementation of our ”perception-guided path planning” paradigm, applying the two functions of decision. Our approach is implemented according to three steps:

• **1st step:** Computation of the current best path (classical D* processing) and determination of the current access frontier (figure 9), using the decision function we defined in section III-B.2

• **2nd step:** Selection of the most promising node of the access frontier (figure 10): this is the heart of our approach. The principle is to assess the nodes belonging to the access frontier in order to find the best next place where to perform the next perception action. This best node is then targeted as an intermediary sub-goal that

Fig. 9. 1st step: access frontier computation

the rover should reach in order to be able to perform the planned perception. Each frontier's node is assessed individually by performing an on-line "simulation" of the perceptions that could be performed from this node, with applying the model of perception described in section II-B. This gives rise to an increase of the COP onto the simulated perceived area of the map. This COP modification will directly act onto the traversability costs, given that they depend both on the probability distribution over the terrain classes and on the COP, for each node (as defined in section III-A.2).

Fig. 10. 2nd step: frontier points accessability

As a result, D* will be re-processed with the updated traversability map in order to take into account these latest updates. Hence new better paths may be discovered: the new path cost considering a given access node will be computed as the sum of two elements: the path cost from the robot to this node, and the path cost from this node to the final goal, in the "simulated" configuration.

• **3rd step:** Consideration of the geometrical properties of perception (figure 11). Range sensors being mostly directional, we finally have to choose the best possible perception direction from the most promising node (as selected in the 2nd step). A large panel of heuristics may be used to do so. In our approach, the direction selection is mainly performed according to the two following criteria:

Fig. 11. 3rd step: perception direction selection

- the possible perception directions should be restrained to the directions so that the n first nodes of the new path should be included into the perceived area of the map.

- among the remaining (discrete) available directions, we compute the whole perception interest for each possible corresponding perception (using the TDU results as detailed in section III-B.1): the selected perception will be the one that maximizes the perception interest.

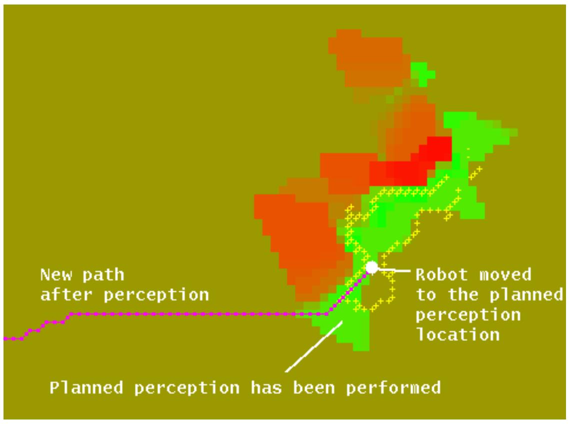

Fig. 12. Application of the planned perception

The robot finally moves to the planned perception location, then performs the planned perception (figure 12).

IV. Results and future works

PG2P's performance depends basicaly on the terrain where the robot has to navigate. As a result, PG2P does not give better results than usual optimal path planning approaches when the environment is sparse and "easy to cross": in other words, if the way computed by D* turns out to be the best possible way (a posteriori) considering the whole terrain map, then PG2P will usually return suboptimal results (when the path computed by D* from an initially unknwon map turns out to be the same that the path computed in the corresponding known map). On the contrary (figure 13), if the terrain is rather cluterred and so D* computes a path that is far to be the "a posteriori best one", then PG2P turns out to be interesting:

in such cases, our tests show results about 20% better than D* in terms of final path cost (with paths length up to 400 meters and a 0.7 meters pitch grid). As said in introduction, PG2P does not aim at concurencing dynamic path replanners: it is an approach that focuses on linking path planning and perception planning. As a result, PG2P is far more cpu-consumming than path planning only: full planning's cycle computation currently requires up to several seconds, depending on the size of space to check around the robot (most of the time being spent for the successive calls to D* when assessing the cost of the access frontier nodes). However time or cpu consumption is not a major concern in our scheme: the time required for the robot navigation between sub-goals corresponding to planned perceptions locations may be exploited for perception planning purpose. Moreover, we expect to get soon sub-second planning time with optimizing our implementation of the PG2P algorithm.

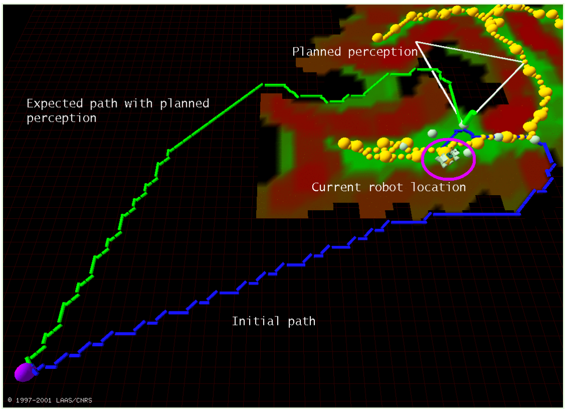

Fig. 13. PG2P in simulation

PG2P is on the way to be hosted onto two rovers using stereo cameras for perception: Lama, a marsokhod-like rover that has already been using a basic D* for 1 year (figure 14), and Dala, an iRobot ATRV rover.

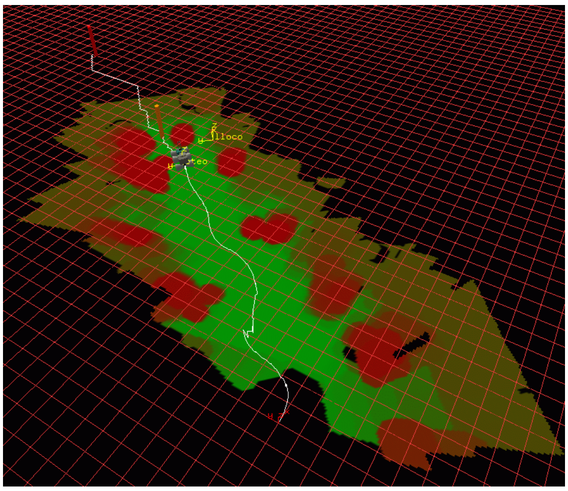

Fig. 14. D* planning in real experiments

V. Conclusion

We presented a paradigm called perception-guided path planning (PG2P), which is an hybrid approach between navigation and exploration considering in a single process both path planning and perception planning so that the most relevant perceptions (regarding the goal to reach) may be performed. Even if the computed path is globally suboptimal, results show that this approach may bring benefits in terms of path cost when compared to a pure path planning approach, especially when the environment is rather cluttered. From our point of view, this approach takes place into a more global effort aiming at providing robots with software means and efficient tools for extending their autonomy in terms of decisional capabilities, toward long range autonomous navigation.

VI. References

[1] R. Bajcsy,"Active Perception". In *Proceedings of the IEEE*,VOL.76,NO.8, 1988

[2] D. Bonnafous, S. Lacroix, and T. Siméon, "Motion generation for a rover on rough terrains". In *proceedings of the International Conference on Intelligent Robots and Systems, Maui, Hawai (USA)*, 2001.

[3] R. Chatila, S. Lacroix, T. Siméon, and M. Herrb, "Planetary exploration by a mobile robot: Mission teleprogramming and autonomous navigation". In *Autonomous Robots Journal*, 2(4):333–344, 1995.

[4] H. Chernoff, L. E. Moses, "Elementary Decision Theory". Dover editions, Mineola, USA, 1986 (first publication: J. Wiley & Sons, New-York, 1959)

[5] A. Elfes,"Dynamic Control of Robot Perception Using Multi-Property Inference Grids". In *Proceedings of the 1992 IEEE International Conference on Robotics and Automation*,Nice,France, 1992

[6] S. Koenig, M. Likhachev,"D* Lite". In *Proceedings of AAAI/IAAI*,476-483, Edmonton, Canada, 2002

[7] A. A. Makarenko, S. B. Williams, F. Bourgault, H. F. Durrant-White, "An Experiment in Integrated Exploration". In *Proceedings of the International Conference on Intelligent Robots and Systems*, Lausanne, Switzerland, 2002

[8] R. Simmons, D. Apfelbaum,W. Burgard,D. Fox, M. Moors, S. Thrun, H. Younes ,"Coordination for Multi-Robot Exploration and Mapping". In *Proceedings of the National Conference on Artificial Intelligence*, Austin,USA, 2000

[9] S. Singh, R. Simmons, T. Smith, A. Stentz, V. Verma, A. Yahja, and K. Schwehr, "Recent Progress in Local and Global Traversability for Planetary Rovers" In *Proceedings of the International Conference on Robotics and Automation*,San Francisco, USA, 2000.

[10] A. Stentz,"Optimal and efficient path planning for partially known environments". In *Proceedings of the International Conference on Robotics and Automation*, 3310-3317, San Diego, USA, 1994

[11] A. Stentz,"The Focussed D* Algorithm for Real-Time Replanning". In *Proceedings of the 14th International Joint Conference on Artificial Intelligence*, 1652-1659, Montreal, Canada, 1995

[12] B. Yamauchi,"A Frontier-Based Approach for Autonomous Exploration". In *Proceedings of the International Symposium on Computational Intelligence in Robotics and Automation*, Monterrey, USA, 1997