Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-23 (2016) 226–231

Integration of risk in hierarchical path planning of underwater vehicles

Nicolas Lefebvre * **Ingrid Schjølberg** * **Ingrid B. Utne** *

* *Department of Marine Technology, Norwegian University of Science and Technology (NTNU), NO 7491 Trondheim, Norway (e-mail: nicolas.lefebvre@ntnu.no, ingrid.schjolberg@ntnu.no, ingrid.b.utne@ntnu.no)*

Abstract: This paper focuses on path planning problems integrating the risk of collision. This challenge is crucial regarding the use of autonomous underwater vehicles (AUVs) for inspection, maintenance and repair operations. The solving of this problem in a reasonable amount of time enables integration of path planning in the AUV control architecture and, by this way, enhances its autonomy capability. Classical approaches rely on the A-Star algorithm to solve this problem, but the heuristic associated to the collision risk appears to be inefficient in some cases. Based on the hierarchical technique, i.e., HPA-Star, another approach is proposed. It leads to paths close to the optimal ones calculated in a faster way. The performances are illustrated in the context of a multi criteria optimization: minimal length and minimal risk path planning.

Keywords: Path planning, Probabilistic risk assessment, Multiobjective optimisations, Autonomous vehicles, Hierarchical decision making

1. INTRODUCTION

In underwater inspection, maintenance and repair (IMR) operations, the use of autonomous underwater vehicles (AUVs) as an alternative to remotely operated vehicles (ROVs) constitutes a significant potential for saving costs. The benefits are particularly related to the ability of autonomous systems to operate without the support of a surface vessel, see Winnefeld and Kendall (2011).

AUVs are exposed to random environmental conditions and operational hazards challenge risk management of the IMR operations. In this context, a direct approach to risk control is path planning adaptation, specially related to AUV inspection tasks where collision is one of the major undesired events. This gives significant advantages compared to existing systems which mainly optimize the path planning on minimal cost or operational time.

Bae et al. (2015) consider the problem of finding a risk-constrained shortest path for an unmanned combat vehicle. The problem is solved by the use of a dynamic programming approach. The problem of computational time is tackled by a straightforward limitation of the explored area. Pereira et al. (2013), as Greytak and Hover (2009), use the A-Star algorithm to find the minimum risk path for an AUV or underactuated surface vessel. Path length and risk is discussed, but no solution is suggested to balance out the inefficiency of the considered heuristic in A-Star. De Filippis et al. (2011) discuss the use of A-Star and genetic algorithm to find minimal risk path.

The objective of this paper is to present an approach for risk-based path planning. Its main contribution is to propose a trade-off between computational requirements and the optimality of the found path to enable embedded integration of path planning in the AUV control architecture. This is obtained through the hierarchical path planning methodology.

The remainder of this paper is organized as follows: section 2 gives an overview of risk and general considerations on how risk can be associated with the path planning task. Section 3 focuses on path planning algorithms and definition of heuristics. Section 4 presents the case study. Section 5 provides computational experiments to illustrate the developed strategy. Finally, the article ends with concluding remarks and perspectives.

2. RISK IN PATH PLANNING

The aim of this section is, firstly, to provide a brief introduction to risk. Secondly, to discuss the interactions between risk and AUV control and especially the path planning. Moreover, risk assessment along a path is presented.

2.1 Risk

According to Kaplan and Garrick (1981) and Rausand (2011), risk analysis answers three main questions: 1. What can go wrong? 2. What is the likelihood of that happening? and 3. What are the consequences? Let risk be defined as a set $R = \{(E_i, \Pr\{E_i\}, C_i)\}_{i=1}^{n_R}$ of n_R triplets where E_i denotes the hazardous event i, $\Pr\{E_i\}$ the probability of occurrence of this event and C_i the cost associated to its consequences. The risk management framework, proposed in ISO 31000 (2009), describes the steps to identify the set R. If all hazardous events have been considered and included, the set is considered to represent risk.

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.10.347

Let $r_T = \sum_{i=1}^{n_R} C_i \mathbb{I}_{\{E_i\}}$ be the random variable which characterises the cost associated with the occurrence of the hazardous events. The total risk R_T is defined as the mean value of r_T:

$$R_T = \mathrm{E}\left[r_T\right] = \sum_{i=1}^{n_R} C_i \mathrm{E}\left[\mathbb{I}_{\{E_i\}}\right] = \sum_{i=1}^{n_R} C_i \mathrm{Pr}\left\{E_i\right\} \qquad (1)$$

Part of the hazard identification process may focus on deriving risk influencing factors (RIFs). RIFs can be defined as an aspect (event/condition) of a system or an activity that affects the risk level of this system or activity, see Oien (2001). For AUVs, RIFs and hazardous events are related to the operation of the vehicle, i.e., the technical condition of the AUV, its mission and operating context. Collision is one important hazardous event to mitigate for path-planning. Hence, to limit the extent of the paper, the path planning approach is exemplified by focusing on collision risk.

2.2 Integration of risk in path planning

Referring to National Research Council (US) (2005), an AUV is a vehicle that possesses self-governing capabilities allowing it to carry out tasks without human intervention.

According to Campbell et al. (2012), a simple way to integrate risk is at the supervision level, through the adaptation of the vehicle path to the safety requirements. Basically, this task is achieved off-line on the basis of a mapped environment with known static obstacles, but it can also be considered on-line to enhance the AUV's autonomous capabilities. Therefore, one of the challenges is to carry out this new capability in combination with standard reflexive avoidance strategies. Another one is to provide path (re)planning solutions in accordance with the computational capabilities and time constraints intrinsic to the embedded system in AUV applications.

The aim of the proposed approach is to provide a solution for path planning, with risk integration, compatible with an embedded use, i.e., with limited computational requirements. A mapped environment with known static obstacles is assumed. The start and goal position, as well as weights put on the different criteria considered for path planning might be provided by the AUV itself, increasing by this way its autonomy.

In the next section, the path planning problem and the integration of risk is formalized.

2.3 Problem formalization

Path (or motion) planning is the subject of an extensive research. For an overview, see, for instance, LaValle (2006) or Paull et al. (2013). The general problem statement is to find a *path* between the given start and goal *states* (i.e., positions). Generally, this problem is associated with the optimisation of a performance criterion (e.g., path length, travel time) and is potentially subject to constraints (e.g., path smoothness). So, risk integration in path planning can be seen as adaptation of the performance criterion or of the constraints.

There are several approaches to achieve the path planning: e.g., potential fields, sampling-based (randomized) approaches, combinatorial (deterministic) approaches. To avoid the inherent problem of potential fields to get trapped in local minima and the intrinsic weaker of random approaches (near optimal solution if a solution is found), the combinatorial approaches and especially heuristic based algorithm are considered in the following. Therefore, it is assumed that the continuous vehicle environment (i.e., the search space) can be modelled as a graph $G = (S, T)$ where $S = \{s_1, s_2, \ldots, s_n\}$ is the set of possible state (e.g., locations of the vehicle) and $T = \{(s_i, s_j) : s_i, s_j \in S, s_i \neq s_j\}$ the set of possible transitions between states S. All transitions in T can be weighted with several non negative values (e.g., length, travel time, risk).

Path planning corresponds to the search in G of a path from a starting state s_s to a goal state s_g ($s_s, s_g \in S$). A path $p_{s_s,s_k} = [s_s, s_i, \ldots, s_j, s_k]$ defines the successive states that have to be reached to go from the starting state s_s to the state s_k. In the following, path p_{s_s,s_k} is noted p_{s_k} if the starting state is s_s; $p_{s_k}(i)$ denotes the i^{th} states reached and $|p_{s_k}|$ is the number of states in the path. Path planning can be formulated as an optimisation problem

$$p^*_{s_g} = \underset{p_{s_g} \in \mathcal{P}_{s_g}}{\arg\min}\ g\left(p_{s_g}\right) \qquad (2)$$

where $p^*_{s_g}$ denotes the path, amongst the set $\mathcal{P}_{s_g}$ of possible paths from s_s to s_g, that minimizes the cost function g. Constraints may be added to (2), e.g., $f^{(i)}(p_{s_g}) - f^{(i)}_{th} < 0$ where $f^{(i)}, i = 1, \ldots, n_c$ is a set of cost functions and $f^{(i)}_{th}$ a set of specified maximal threshold. Through this formulation the path planning problem may be formulated as the search of *i)* the minimal length path, *ii)* the minimal risk path, *iii)* the minimal length (respectively risk) path subject to a constraint of a maximal level of risk (resp. length) in the set $\mathcal{P}_{s_g}$.

2.4 Cost assessment along a path

Several cost functions g, depending on the criteria considered for path planning (length and risk), are defined in the following.

Path length is defined by (3) where the distance associated with the transition from state $p_{s_g}(i-1)$ to state $p_{s_g}(i)$ is denoted by $d\left(p_{s_g}(i-1), p_{s_g}(i)\right)$.

$$g_{length}(p_{s_g}) = \sum_{i=1}^{|p_{s_g}|-1} d\left(p_{s_g}(i), p_{s_g}(i+1)\right) \qquad (3)$$

Regarding risk, as mentioned before, we focus only on the risk of collision. Moreover it is assumed that whatever is the collision consequence, it leads to a constant cost C_{C_o} and aborting the mission. Therefore, only the first collision is of interest.

Consider the function $C_o(s_i, s_j)$ which equals 1 if there is collision in the transition from the states s_i to s_j with $(s_i, s_j) \in T$ and equals 0 if not. Let $\Pr\{C_o(s_i, s_j) = 1\}$ be the probability that a collision occurs during this transition. Such quantity is associated with all transitions in the set T of G. Due to the sequencing of displacements, the risk associated with the path p_{s_g} corresponds to the product of the cost C_{C_o} with the probability that: