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Risk space modelling for human-robot collaboration in a shared intralogistics scenario

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***Abstract*—This paper aims to define a multi-dimensional risk space for a robot moving in a shared environment with human operators. The dimensions of the risk space are defined as the risk factors which may lead to an undesired event. An analysis of the robot state variables on which each individual risk source may depend leads to the introduction of a fuzzy inference system to quantify the risk levels in the particular case study. The methodology presented in this paper outlines a general way to characterize risk for autonomous agents working in partially unknown environments, which generalizes to most human-robot collaboration scenarios. The proposed framework is also flexible to the introduction of new risk factors.**

***Index Terms*—risk assessment, human-robot collaboration, risk-aware motion planning**

I. INTRODUCTION

Based on the current literature, in a human-robot collaboration scenario, the risk is intended as the hazard the robot poses to the external world, in particular to the human operator in compliance with the collaborative robot safety specifications [3]. However, according to the risk management literature, risk is defined as the likelihood of a detrimental event occurring to a project [1], [2], that becomes the desired task for a robot. In an intralogistics scenario, there are not just risks related to the operator's safety but also risks of collisions with fixed and moving obstacles (e.g., forklifts), risks of delays in respect of settled deadlines (e.g., fetching an item that is coming from a conveyor belt), and risks related to the robot's self-safety (e.g., overheating, vibrations). Therefore, there is a need to broaden the concept of risk to include all the detrimental events that may prevent the task's success. This work aims to identify the main risk factors involved and propose a map to quantify the risk levels both offline and online. Minimizing a risk function that depends not only on safety measures but also on performance indexes (e.g., the execution time for the delay risk) will allow obtaining robot trajectories that allow the robot to execute the desired task while guaranteeing efficiency and safety.

II. CONTEXT DEFINITION

The considered use case scenario is an intralogistics warehouse, where mobile robots and humans operate in a shared environment without physical barriers. In particular, the considered robot is a 7 DoF (Degree of Freedom) PANDA manipulator mounted on an omnidirectional mobile platform. The task consists in going to shelf A, picking the desired item, and bringing it to tray B. When approaching B, the robot may throw the object into the target or place the object directly in the tray, if the throw failure risk is too high. We can decompose the task into three phases, in which we will have different risk factors:

- *Navigation phase*: In this phase, the mobile base moves the robot to reach the right shelf or to deliver the items.
- *Picking and placing phase*: In this phase,and the robotic arm performs the pick (or place) operation.
- *Throwing phase*: In this phase, the manipulator moves to reach the best throwing configuration.

III. RISKS IDENTIFICATION AND ASSESSMENT

To identify the involved risk factors we developed and merged independent lists, including suggestions and inputs from industry partners of the European Project DARKO.

We cataloged the most relevant detected risk factors within the following families:

- *Performance risks*: Risks concerning the quality of the task execution. (e.g., excessive power consumption leads to increased costs and fewer tasks that can be performed in a charge cycle, and delay in fetching an object from a conveyor belt can cause the assigned task to fail);
- *External risks*: Risks related to the damage that the movement of the robot can cause to other agents involved in the tasks or near the robot (humans, obstacles), in compliance with the ISO/TS 15066;
- *Internal risks*: Risks related to the damage that the robot movement can cause to the robot itself (e.g., damage to the motors due to vibration or overheating, self-collisions between the manipulator and the moving base).

Every detected risk represents a "risk factor" in our multi-dimensional "risk space". The risk level of each risk factor can be expressed quantitatively by combining the probability that the hazardous event occurs and its severity [1], [4].We use a Takagi-Sugeno-Kang fuzzy inference system to map probability and severity to a scale that quantifies the risk level. In this way, the map on the risk scale is continuous. We defined five levels for probability (Almost Impossible, Low, Medium, High, Almost certain), and four for severity (Minor, Moderate, Severe, Catastrophic). We chose trapezoidal membership functions and a structure-oriented approach to generate the fuzzy rules. For each risk factor, the risk level span between 0 and 6.

Of course, not all risks may assume all the possible severity levels, and only the risks addressing human safety may reach the catastrophic level.

To compute probability (or severity) for each risk, we propose another fuzzy inference system. This system would have as inputs the variables on which the probability (or severity) of the risk depends. The output will be the sought-after value of probability or severity, which will then enter the risk level inference system, thus creating a fuzzy tree. However, if a more accurate metric to quantify probability or severity for a specific risk is available, the obtained value can be used directly in the risk level inference system. This approach allows a single framework with heterogeneous metrics.

IV. Planning minimizing risk

In this section, based on the previously defined level of individual risk factor, we propose an overall index that takes into account all possible risks encountered by the robot during the task execution.

We express the global risk index as a RealSoftMax function of the concurrent risk factors.In this way, it is possible to penalize high levels of risk but to still distinguish between one system state where all risk levels assume the same value (e.g., two) and one where only one risk assumes the maximum value (e.g., only one risk level is two and the others are zero or one), with the former representing a more dangerous state.

$$\text{Global Risk Index} = \log(\sum e^{\text{risk factors}}) \tag{1}$$

As a first attempt to compute the reference risk-driven offline trajectories for the manipulation phase, we propose to solve the problem with a genetic algorithm, where the fitness function is the Global Risk Index (GRI) defined above (considering the maximum value reached from each risk index along the trajectory), with a few additions: lim is a strongly penalizing term if the kinematic limits of the robot (speed, accelerations, jerks) are exceeded, $\|x_f - \hat{x}_f\|_2$ it's the distance between the real and the desired final point, and sl that is the generated End-Effector (EE) spline length.

$$\text{Fitness Function} = 1000{*}\|x_f - \hat{x}_f\|_2 + 10{*}\text{sl} + \text{lim} + \text{GRI} \tag{2}$$

We take as variables ten positions for each joint (so seventy variables 10x7) and the ten instants of time in which the robot will reach these positions (other ten variables), so in total, we have 80 variables. The calculation of the terms present in the fitness function is carried out by interpolating joints' position values and the times at which they are reached with cubic splines. Then, we find a B-spline which approximates the EE trajectory, resulting from direct kinematics, and we use it to evaluate the task space related risks.

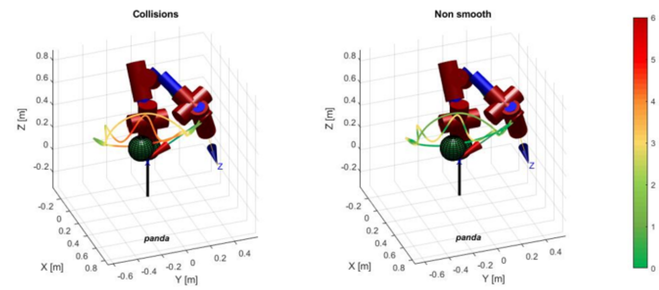

Fig. 1. Levels of collisions with fixed obstacles and non-smooth path along the planned trajectories after 1, 5, 150 generations, using the genetic algorithm approach, during the manipulation phase. The initial population contains a good solution, but it does not take into account the presence of the known offline obstacle (the dark sphere). After 5 generations, the algorithm starts to avoid the obstacle, but the resulting trajectory is not particularly smooth. After 150 generations, the algorithm found a good solution that guarantees collision avoidance while keeping the other risk values low.

V. Results

The identified risks during the three motion phases have been reported in tables including a description of the hazardous situation, the family to which the risk belongs, and the planning stages in which the risk should be assessed and minimized (offline motion planning, task scheduling, online trajectory modification during path execution). For each identified risk, the levels of severity were indicated as well as a precise definition was given. Risk factors were then analyzed, underlining the state variables and the parameters on which probability and severity depend for that risk. From the variable and the parameter values, fuzzy logic inference systems are used to assess the probability and severity values. The genetic algorithm approach for the manipulation trajectory generation was tested for an offline planning scenario with fixed initial joint configuration q_0 to reach a desired final position in the task space x_f in the presence of a fixed obstacle (see Fig. 1).

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