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REGULAR PAPER

Automatic evaluation of planners in dynamic scenes during human–robot interaction

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Abstract
The evaluation of planners is essential to guarantee the efficiency and performance of trajectories executed by collaborative robots in human–robot interaction (HRI) contexts. The main objective of this research is to develop a method that allows obtaining an automated assessment of the performance of planners widely used in robotic environments. In addition to analyzing specific metrics such as planning time, path length, smoothness, and clearance, this paper introduces novel contributions, including a unique method for dynamic scene evaluation and a new comprehensive and global performance index, named Total Performance Index (TPIx), which encompasses all the aforementioned metrics. The system proposed is composed of a collaborative robot and an RGB-D sensor to monitor the environment using 3D data to perform safe trajectories during multiple tasks. In this quantitative evaluation, two single-query planners (RRT, KPIECE) and two multiple-query planners (SPARS, PRM) were analyzed. The results obtained demonstrate the feasibility and effectiveness of the proposed method to automatically evaluate the planners used by collaborative robots. Therefore, this study contributes to the advancement of collaborative robotics by introducing updated methods for planner evaluation and aims to facilitate the development of more efficient and adaptive systems in light of recent advancements in robotic technologies.

Keywords Collaborative robot · Human–Robot interaction · RGB-D data · Safe path planning · Planners

1 Introduction

The exponential evolution of technology in recent decades has led to the consolidation of robotics in countless practical applications that directly affect our daily life. In particular, Human-Robot Interaction (HRI) has become an area of interest due to its application in various fields such as industry, medical assistance, home, research and exploration, among others (Tsarouchi et al. 2016; Kumar et al. 2022). Given the increasing need for robots that can coexist and collaborate efficiently with human beings in shared environments, it is imperative that robots are able to adapt and react adequately to dynamic scenarios that are constantly changing due to human intervention or unforeseen external factors. It is important to mention that HRI faces numerous challenges such as safety in HRI, user trust, usability, adaptability and natural interaction (Olaronke et al. 2017).

A planner is a system or algorithm that allows a robot to generate a sequence of actions to achieve a specific goal. Therefore, automatic planning plays a crucial role. An effective planner is one that allows the robot to make quick and accurate decisions in real time, anticipating and adjusting to human actions and variations in the environment. However, the evaluation and validation of these planners in dynamic scenes remain a considerable challenge for the scientific community. This study aims to address this gap by providing an updated analysis of methods and tools to automatically

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evaluate the efficiency and effectiveness of planners in HRI environments, incorporating recent advancements and addressing the challenges highlighted by contemporary research. Efficiency in planners refers to their ability to use computational resources such as time and memory optimally while generating action sequences. Effectiveness, on the other hand, measures how well the planner achieves its intended goals, particularly in dynamic and unpredictable human–robot interaction (HRI) scenarios. By focusing on both aspects, the study seeks to ensure that planners are not only fast and resource-efficient but also capable of producing accurate and reliable outcomes in real-world applications.

Throughout this article, we will explore the intrinsic challenges that dynamic scenes present in human–robot interaction, discuss existing methodologies and present new proposals and tools for the automatic evaluation of planners in this context. It is important to mention that a first exploration was carried out by examining several planners in the context of a static scene (Hernández et al. 2023), this study is established as the starting point for the current research. This analysis lays the groundwork by reusing crucial settings such as camera calibration, experimental setup, and point cloud processing. Additionally, a list of planners widely used by collaborative robots is incorporated, thus outlining the direction of our work. The proposed study aims to lay the foundation for the development and optimization of safer, more responsive and cooperative robots in dynamic environments shared with humans.

Additionally, this research provides a method to facilitate automated evaluation of the effectiveness of planning systems widely used by collaborative robots. For this purpose, a method is proposed based on the assessment of specific metrics, such as: planning time, path length, smoothness and clearance. In addition, an innovative global performance index is presented that incorporates all the aforementioned metrics, this index is called Total Performance Index (TPIx). The system proposed in this research is composed of a collaborative robot and an RGB-D sensor to monitor the work environment using 3D data (point cloud and depth map).

This research introduces a novel method for the automated evaluation of safe human–robot interaction, which has been rigorously tested within collaborative environments where operator safety is paramount. The proposed system combines real-time perception and planning to proactively prevent collisions between the robot, the operator, and any objects in the workspace. Central to this approach is an intelligent robotic system, featuring a collaborative robot equipped with an RGB-D sensor for 3D environmental monitoring. The system not only generates and executes safe trajectories but also systematically assesses the effectiveness of the planners guiding the robot.

To validate the proposed system, the developed code and the new index (TPIx), two test contexts were proposed. The first context is working with a static scene, that is, there are no changes in the work environment, only the collaborative robot performs the movements. For this scenario, three experiments were proposed, for each experiment the robot executes multiple trajectories from point A to point B. During the execution of the trajectory, the different metrics and the TPIx index are calculated. The second context proposes a dynamic work scene, where in addition to the movements made by the collaborative robot there are also changes to the work environment, for this scenario a basic task is proposed, which consists of the participant must reach the end effector of the collaborative robot, for this reason a mobile device was incorporated into the end effector, this mobile device has a mobile application that is synchronized with the collaborative robot and guides the participant to the start and end of the reach task.

The article is organized as follows: The Sect. 2 presents the related works. In Sect. 3, the materials and methods used in the approach are described. The experimental setup is explained in the Sect. 4. In the Sect. 5 the results obtained are analyzed and discussed. Finally, the conclusions and future work are described in Sect. 6.

2 Related work

Human-robot interaction (HRI) is a current topic of research in which many researchers have been working for many years, especially in the field of industry (Tsarouchi et al. 2016). The type of interaction between the human and the robot classifies HRI in four different types of cooperative robot operations (Hentout et al. 2019): safety-rated monitored stop (SRMS), hand guiding (HG), speed and separation monitoring (SSM), and power and force limiting (PFL). These cooperative operations between the human and the robot can be defined as contact (PFL) and non-contact (HG, SRMS, SSM) operations. Collaborative robots perform the implementation of these HRI strategies more easily than a conventional industrial robot manipulator.

Various approaches, especially in the field of industry, address this problem by using depth information to calculate the distance between the robot and the human in the environment in real time by tracking the human position and obtaining the robot configuration from the controller (Secil and Ozkan 2022). To calculate HRI parameters, human and robotic geometries are represented in different types of shapes such as capsule-shaped geometric primitives (Safeea and Neto 2019). There are also studies where human detection is performed using depth and baseline data captured by RGB-D Kinect cameras (Nikolakis et al. 2019; Melchiorre et al. 2021). In these cases, the point cloud is usually first converted to a 3D *octree map* and then represented as a convex hull for use in the 3D map to calculate the distance between humans and robots. There are other approaches that implement a multisensory system using information obtained from the camera and the sensors IMU (Meziane et al. 2014; Zhang et al. 2020). Collaborative robots are also used in healthcare settings to assist with tasks such as transporting supplies, disinfecting areas, and rehabilitating patients. In Mandischer et al. (2023) a generalized approach is proposed towards the inclusion of collaborative robots and considering person factors such as fast effects (e.g. fatigue) and slow effects (e.g. worsening of the disease). The inclusion of robotics in collaborative environments poses many challenges, where there may be close contact in highly sensitive areas of the operator's body. Therefore, it is of utmost importance that the system has the ability to plan the robot's movements and avoid collisions. In this context, studies have been proposed in which external sensors such as RGB-D cameras and specialized software are incorporated to avoid collisions and thus achieve safe trajectory execution (Uccheddu et al. 2022). Dumonteil et al. (2015) describes how obstacles could be detected and avoided using a single Kinect sensor to monitor the workspace and the *KineoWorksTM* software library's reactive planner for real-time selection of an avoidance trajectory. In Scimmi et al. (2021) using two Kinect sensors whose information is combined and then given as input to the collision avoidance algorithm, the experimental results of this study show the effectiveness of the collision avoidance algorithm and the significant gain in terms of task times that the highest level of collaboration between humans and robots.

This research aims to contribute to HRI through the automatic evaluation of the planners used by collaborative robots. Additionally, the proposed system is analyzed in dynamic environments, to ensure adequate and safe collaboration between the operator and the robot. It is expected to lay the foundations to ensure adequate HRI in collaborative environments, combining a natural experience for humans and the adaptability of robotic systems.The main contributions of the presented approach can be summarized as follows:

1. Benchmark study of the planners available in OMPL using MoveIt for upper limb rehabilitation exercises.
2. Analysis of processing times for the construction of a highly dynamic system guaranteeing operator safety.
3. Proposal of a new global performance index for the evaluation of planners using different metrics: planning time, path length, smoothness and clearance.
4. Development of a ROS node for computing the planner performance metrics in real time.
5. Base code of a mobile application integrated in ROS, which can be used for various objectives, a possible orientation is focused on rehabilitation exercises and monitoring of the patient's progress.

3 Materials and methods

To achieve an effective Human-Robot Interaction, it is important to ensure the protection of the operator in all phases of operation, which implies executing safe trajectories, i.e., preventing any type of collision. Furthermore, it is crucial to analyze the effectiveness of the trajectories executed by the robot, which are generated by the implemented planning algorithms. The proposed system architecture for this approach is organized as shown in Fig. 1. The components of the proposed system are described in the following subsections.

3.1 Hardware and software

The proposed system architecture utilizes a set of specific hardware components which include: a UR3 collaborative robot manufactured by Universal Robots, a high-performance computer equipped with an Intel i7 2.60GHz, 16GB of RAM, and an NVIDIA GeForce GTX 1650 graphics card. Additionally, the setup incorporates a OnePlus 6 smartphone and an Azure Kinect Camera for advanced interaction and imaging capabilities.

Regarding the software, the following tools are used:

- The Robot Operating System (ROS) is a commonly utilized framework in the field of robotics. ROS Master allows centralizing all the information coming from the different hardware components detailed in the previous section. The tests are conducted using a computer equipped with the ROS Melodic distribution, specifically version 1.14.13, operating on the Ubuntu 18.04.6 Desktop platform(64 bits).
- MoveIt serves as a comprehensive software solution for path planning in mobile manipulation, integrating various functions such as motion planning, manipulation, 3D perception, kinematics, control, and navigation (Chitta 2016). MoveIt is designed to integrate with a diverse array of planning algorithms. Included within its framework are planners like the Open Motion Planning Library (OMPL), Stochastic Trajectory Optimization for Motion Planning (STOMP), Search-Based Planning Library (SBPL), and Covariant Hamiltonian Optimization for Motion Planning (CHOMP) (Planners 2022). The library used in this study is OMPL, which is a library for sampling-based motion planning, containing implementations of many state-of-the-art planning algorithms (Şucan et al. 2012).
- Point Cloud Library (PCL) is an open project for 2D/3D image and point cloud processing. The PCL framework contains a number of algorithms including

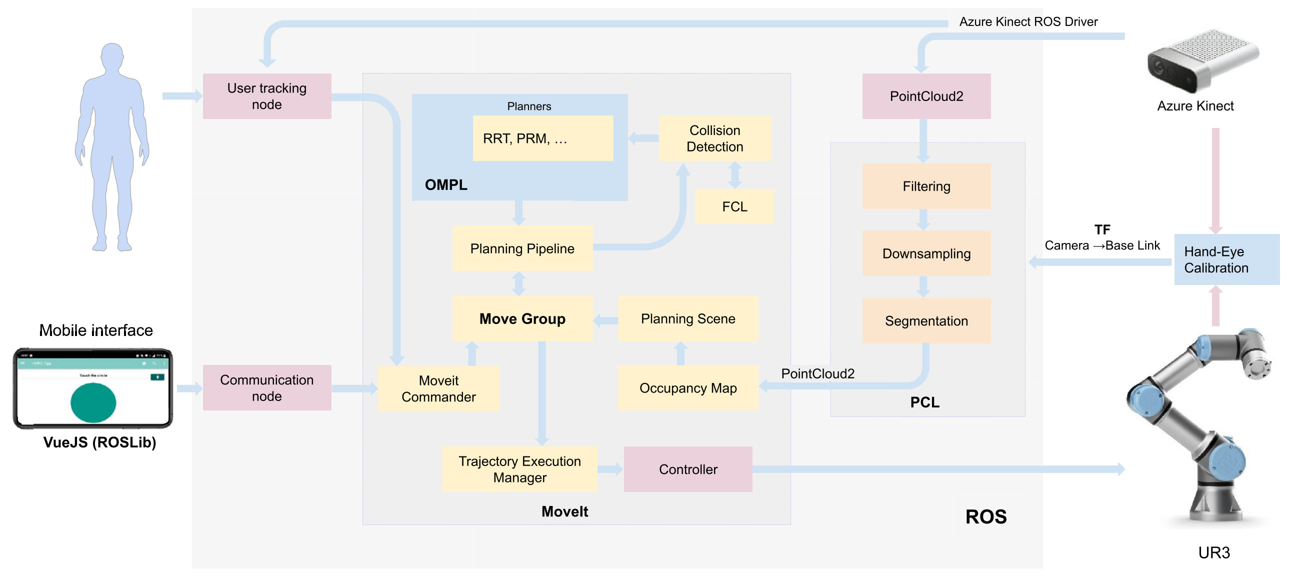


Fig. 1 System architecture

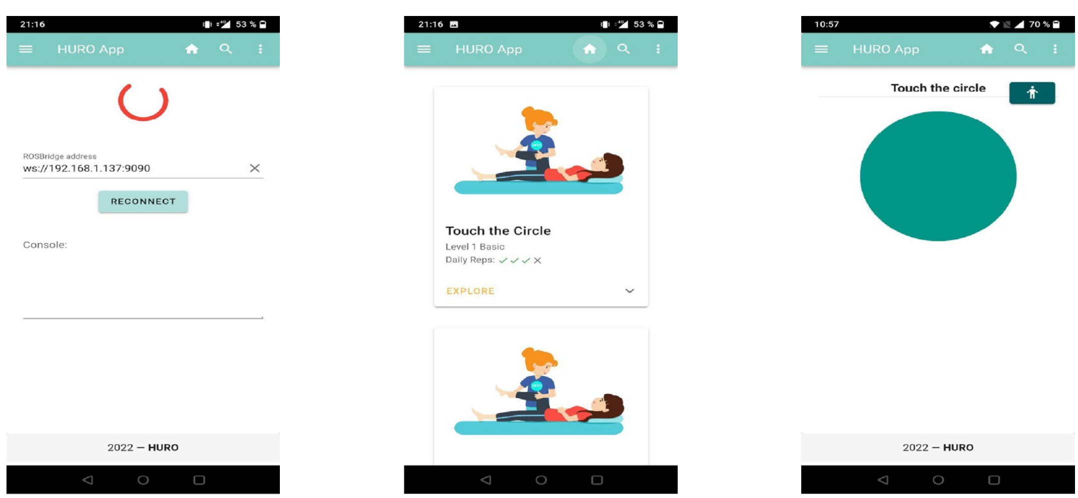
filtering, feature estimation, surface reconstruction, registration, model fitting and segmentation (Rusu and Cousins 2011).

3.2 Mobile application

For managing and monitoring the rehabilitation exercises, a mobile application has been developed and integrated in the ROS node. It is worth mentioning that other alternatives can be used (as for example a physical button located at the end-effector), but with the mobile application there is a higher scalability for adding other types of upper limb movements as well as visualization of the patient's progress. This mobile application has been developed using the VueJS framework and the ROSLib library (roslibjs - ROS Wiki 2022) which allows the communication with the ROS Master (see Fig. 2).

The functional requirements implemented in this application are summarized as follows:

- Connection with the ROS Master.
- Tasks list.



(a) Connection with ROS Master

(b) List of rehabilitation exercises

(c) Rehabilitation exercise for this study

Fig. 2 Mobile App

- Rendering of the target. The target is represented by a green circle, on this screen the information is captured and processed using the touch event of the mobile device.

3.3 Path planning

Planning involves the challenge of finding a continuous trajectory that links a robot's starting point with its intended target, ensuring compliance with specific constraints such as collision avoidance, force limitations, and acceleration bounds. The Open Motion Planning Library (OMPL) encompasses planners that utilize random sampling techniques. These planners approach the problem by sampling the robot's state space, aiming for a rapid solution to the planning challenge. Sample-based planners are broadly categorized into two groups: multi-query (relying on roadmaps) and single-query (based on tree structures) planners (Şucan et al. 2012). This study is aimed at evaluating the performance of two single-query planners (RRT, KPIECE) and two multi-query planners (SPARS, PRM). The reason for choosing these four algorithms for the tests was because they are widely used in path planning and they can also be inserted into the dynamic collision avoidance system (Brito et al. 2017). The description of each method is shown below:

Rapidly exploring Random Trees (RRT): The RRT algorithm creates a random tree within the configuration space that is free from collisions. In every iteration, this algorithm augments the tree by incorporating new vertices that are directed towards a configuration chosen at random (Kuffner and LaValle 2000).

Kinematic planning by interior-exterior cell exploration (KPIECE): KPIECE is a tree-based planning algorithm that employs a multi-level discretization approach to navigate the exploration of the continuous state space. The implementation of KPIECE within the Open Motion Planning Library (OMPL) adopts a simplified strategy, utilizing a singular level of discretization through the application of one grid. This grid is applied to a projection of the state space, aiding in structuring the exploration process (Şucan and Kavraki 2009).

SPArse roadmap spanner algorithm (SPARS): The SPARS algorithm has the asymptotic characteristics of completeness and near-optimality. Additionally, the likelihood of incorporating new nodes into the spanner diminishes as the number of iterations escalates, implying the potential existence of finite-sized data structures possessing near-optimal attributes (Dobson et al. 2013).

Probabilistic roadmap method (PRM): The PRM operates through a two-phase planning process: a learning phase and a query phase. During the learning phase, a probabilistic roadmap is developed and preserved in the form of a graph. This graph's nodes represent configurations free from collisions, and its edges denote viable paths connecting these configurations. In the subsequent query phase, specific start and goal configurations of the robot are linked to two distinct nodes on the roadmap. Following this connection, the roadmap undergoes a search to identify a route that connects these two nodes (Kavraki et al. 1996).

3.4 Planning metrics computation

Moveit provides a package to compare motion planning algorithms. However, this comparison does not consider dynamic scene planning. This section describes each of the metrics used in the bechmarking study of the different planners, the new proposed metric (TPIx) and the ROS node to compute the metrics in real time.

The metrics to evaluate the differnte planners are:

Planning time refers to the duration required by planners to execute the motion planning process, encompassing all computational steps involved in this task.

$$T = ppt + it + st + pt \tag{1}$$

where *ppt* is the path plan time, *it* is the interpolation time, *st* is the simplify time and *pt* is the process time.

Path length is determined by summing the distances between consecutive waypoints along the route.

$$L = \sum_{k=1}^{n} d\left(x_{k-1}, x_k\right) \tag{2}$$

where n is the number of waypoints, x_{k-1} is the first waypoint and x_k is the target.

Smoothness in a path is quantified by evaluating the angles at the junctions of path segments, which are formed by creating triangles using consecutive segments of the path. Specifically, this measure involves calculating the angle formed by three successive waypoints along the path.

$$S = \sum_{k=2}^{n-1} \left(2\left(\pi - arccos\left(\frac{d^2_{k-2,k-1} + d^2_{k-1,k} - d^2_{k-2,k}}{d^2_{k-2,k-1} d^2_{k-1,k}}\right)\right)\right)^2 \tag{3}$$

where n is the number of waypoints on the path and $d_{x,y}$ is the distance between waypoints with index x and y.

Clearance is the average distance to the nearest invalid state (obstacle) throughout the planned path.

$$C = \frac{1}{n} \sum_{i=0}^{n-1} cl\left(s_i\right) \tag{4}$$

where n is the number of states on path, s_i is the ith state and $cl()$ is the distance to the first invalid state.

To correctly evaluate human–robot interaction, a new index has been defined to evaluate planners. This new metric is called Total Performance Index (TPIx) (see Eq. 5) which allows identifying the best planner considering the percentage value obtained from the metrics: planning time, path length, smoothness and clearance. Therefore, the planners can be evaluated in a global way considering all the metrics.

$$TPIx = \frac{1}{n}\sum_{i=1}^{n}\left((1-p)V_m + pV_m^c\right) \tag{5}$$

where n is the number of metrics, V_m is the percentage value of each metric, V_m^c complement of V_m and p is the polarity for each metric, $p \in Z\{0, 1\}$. For each metric, a polarity value of $p = 0$ signifies that higher metric values (approaching 1) denote superior performance of the planner. Conversely, a polarity of $p = 1$ indicates that lower metric values (nearing 0) correspond to better performance. The assigned polarities for the metrics are as follows: time is assigned a polarity of 1, path length also has a polarity of 1, clearance has a polarity of 0, and smoothness is assigned a polarity of 1.

The ROS node for computing the metrics in real time receives as input a message of type PoseStamped which includes the position and orientation of the end-effector. To obtain the planning of the robot trajectories, the group name of the manipulator, the end effector goal position, the planner identifier and the kinematics constraints are defined (see Fig. 3). The code of the ROS node and the mobile application is freely available in the following repository: https://github.com/OHernandezr/huro_app_planner_metrics.

During each path planning, this node performs the following tasks:

- Real-time computing of planner metrics: path length, planning time, smoothness and clearance.
- For each iteration the following information is stored: execution sequence, planner name, metric name and metric value.
- Sending the safe execution trajectory to the real robot.

4 Experimental setup

The experimental analysis is performed from two approaches:

1. Static obstacle collision: in this case all performance metrics of the planners are evaluated considering a static work scene. To obtain this evaluation, the tools provided by MoveIt (benchmarking) are used. The benchmarking configuration allows the parametrization of queries, work scenes, storage of results and planners to be evaluated. In order to assess the efficacy of various motion planners under different conditions, three distinct experiments have been designed. Each experiment involves a robotic arm executing two maneuvers while the user's position remains constant. These experiments were repeated 50 times for each motion planner, using identical start and goal state queries in the experimental framework. All planners successfully identified a valid path within the maximum allotted time for the experiment's queries. The focus of this study is the development and analysis of the most suitable plan-

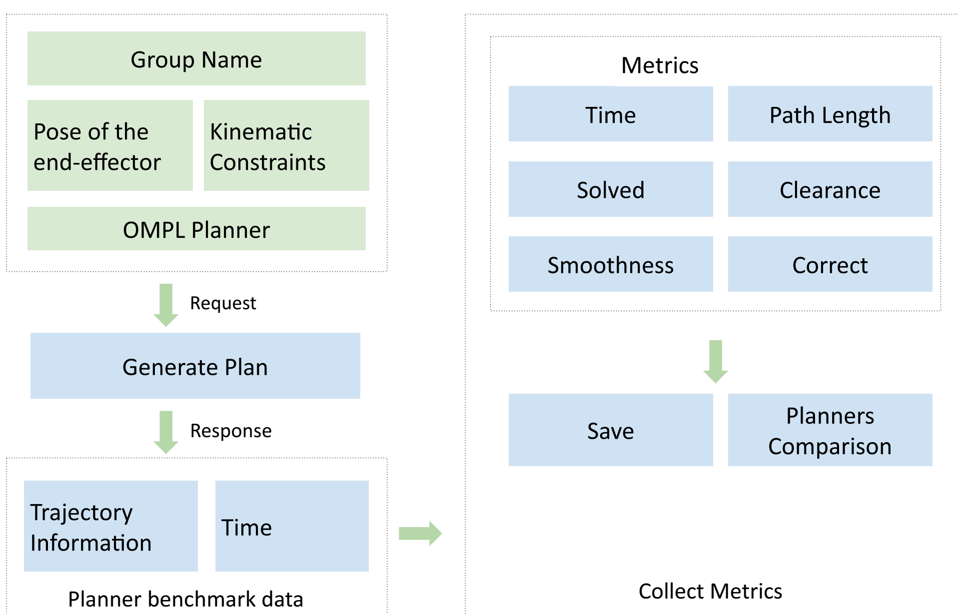


Fig. 3 Planning process and metrics

ner for a safety-centric environment, particularly in scenarios involving upper limb movements associated with reaching motor tasks (end effector of the robot). The experiments take into account several operator positions, including a normal position with arms at rest, maximum frontal extension of the right arm, and maximum frontal extension of both arms (see Fig. 4).

2. Dynamic obstacle collision: in this case all the performance metrics of the planners are also evaluated, however, the work scene is dynamic which considers the different movements made by the participant or any object that is in the work area. To build the Occupancy Map, two possible inputs are considered: PointCloud and DepthMap. In this case, the node provided in this study is evaluated, which performs the calculation of the performance metrics of the planners in real time.

4.1 Scene setup

The planning scene monitor added in MoveIt is responsible for storing the current state of the robot as well as the planning scene, which includes occupancy map information of the robot workspace. The state of the UR3 robot includes an object attached to the end effector, which represents the space occupied by the mobile device. During the trajectory planning and collision verification, three types of objects supported by MoveIt were used:

- Meshes of the real-time representation of the UR3 robot.
- Primitive shapes: table where the robot is located, object at the end effector that represents the mobile device.
- Octomap: dynamic planning scene that includes patient information and any other objects that are located in the working area.

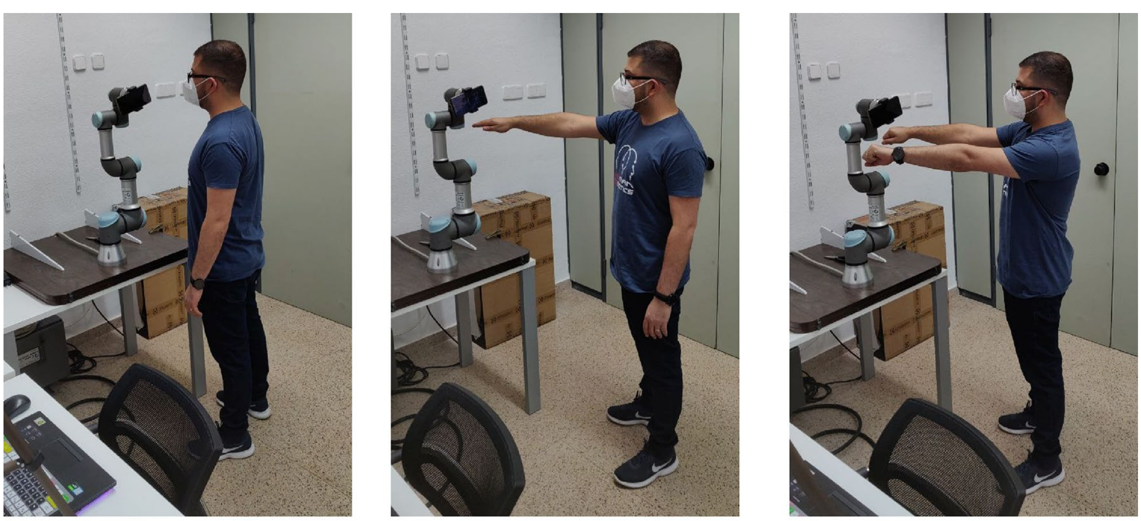
4.2 Robot path planning

The robot is programmed in two modes: Continuous Operator Tracking (1) and Execution of the Reaching Task (2). In mode 1, a mathematical computation of the maximum cartesian movement that the robot can perform is computed, with the system of equations defined by:

$$(x-a)^2 + (y-b)^2 + (z-c)^2 = r^2 \tag{6}$$

$$y - y_0 = m\left(x - x_0\right) \tag{7}$$

In Eq. 6, the variables a, b, c define the center of the work sphere of the robot UR3 that corresponds to the coordinates x, y, z of the base of the robot. The variable r denotes the maximum radius of the UR3 workspace which is 500 mm according to official documentation (Universal Robots 2022). Equation 7 represents the line from the base reference system of the robot to the monitoring point of the patient (see Fig. 5). The intersection point between the workspace of the robot and the line represents the maximum cartesian movement (reaching point) that the UR3 can perform.



(a) (b) (c)

Fig. 4 Experiments performed: **a** Normal position with the arms in a relaxed state **b** Maximum frontal extension of the right arm **c** Maximum frontal extension of both arms

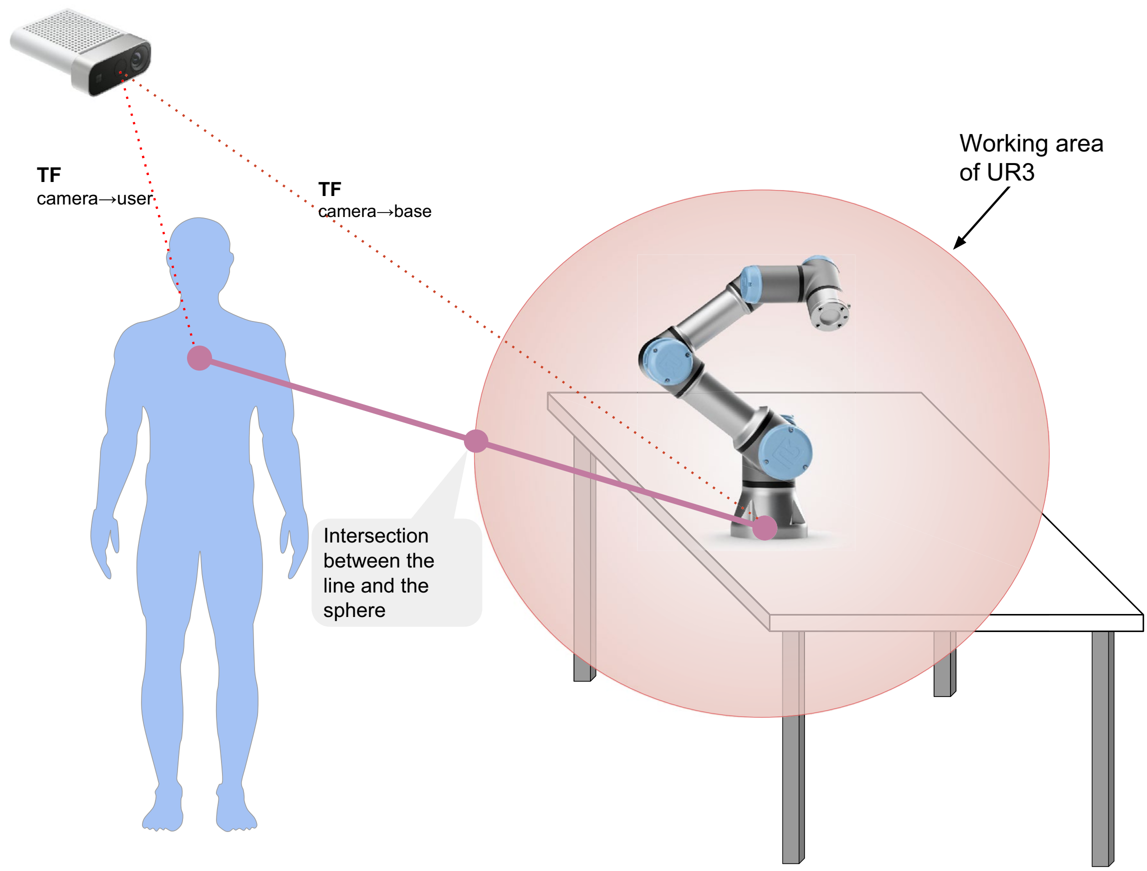
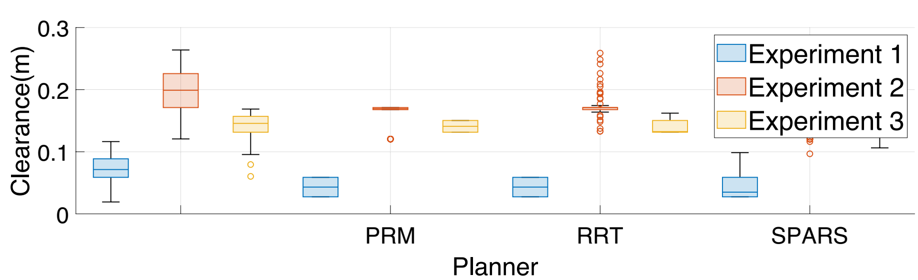


Fig. 5 Maximum movement of the end effector of the UR3 robot

The second mode (Execution of the Reaching Task) is activated immediately when the operator reaches the target for the first time. Once this mode is activated, the robot carries out the following sequence twice: (a) Move end effector 30 cm to the left of the operator and (b) Move end effector 30 cm to the right of the operator. In each movement, the operator must reach the target. Algorithm 1 shows the pseudocode of the main task in the proposed system. In the algorithm, the two modes, (1) Continuous monitoring of the operator and (2) Execution of the reach task, and also the calculation and storage of the metrics during the different tasks can be displayed.

Fig. 6 Average solution of clearance achieved by the planners in a static planning scene



Algorithm 1 Pseudocode of the main task for dynamic environments

```
for Every time step do
    public TF user tracking (Camera RGB-D)
    if Mode 2: Execution of the Reaching Task then
        if Exercise completed in mobile application then
            Calculate the maximum cartesian movement that the robot can perform (Eq.: 6, 7)
            plan ← MoveIt.generatePlan(rehabilitation_exercise)
            CALCULATE_METRICS(plan)
            Move the end effector of the robot according to the user's position (Fig. 5 )
        end if
    else–Mode 1: Continuous Operator Tracking
        plan ← MoveIt.generatePlan(user_tracking)
        CALCULATE_METRICS(plan)
        Move the end effector of the robot
    end if
end for
procedure CALCULATE_METRICS(Execution_plan plan)
    Calculate the planning time (Eq.: 1)
    Calculate the path length (Eq.: 2)
    Calculate the smoothness (Eq.: 3)
    Calculate the clearance (Eq.: 4)
    Store metrics
end procedure
```

5 Results and discussion

5.1 Static obstacle collision

In all experiments, a substantial disparity in planning time (as detailed in Table 1) was noted between single-query and multi-query planners. Single-query planners, such as RRT and KPIECE, demonstrated significantly faster planning times, averaging 20 ms and 84 ms, respectively. In contrast, multi-query planners like PRM and SPARS exhibited notably longer planning times, with averages around 10 s. This difference underscores a critical observation: single-query planners, due to their streamlined approach, provide quicker responses which could be leveraged in time-sensitive applications. However, the extended planning time of multi-query planners might be justified by their ability to handle more complex scenarios.

The clearance metric, which reflects the average distance from the nearest obstacle along the planned path (refer to Eq. 4), serves as a crucial indicator of planner safety, with higher values indicating safer navigation paths. In the third experiment, all planners demonstrated similar clearance levels, indicating a baseline of safety across methods. However, in experiments 1 and 2, while RRT, PRM, and SPARS achieved comparable clearance, the KPIECE planner consistently provided superior clearance results (see Fig. 6). This suggests that while existing planners perform adequately, there is a distinct opportunity to enhance planner safety further. For instance, incorporating advanced obstacle detection and avoidance algorithms into these planners could potentially improve clearance metrics and overall safety. Such advancements are crucial for developing planners that not only meet current safety standards but also push the boundaries of what is achievable in dynamic environments.

Table 1 TPIx result of each planner

Planner	Time(%)	Length(%)	Clearance(%)	Smoothness(%)	TPIx
KPIECE	1.00	1.00	1.00	1.00	0.40
PRM	0.04	0.09	0.84	0.00	0.94
RRT	0.10	0.12	0.87	0.09	0.91
SPARS	0.17	0.16	0.86	0.24	0.86

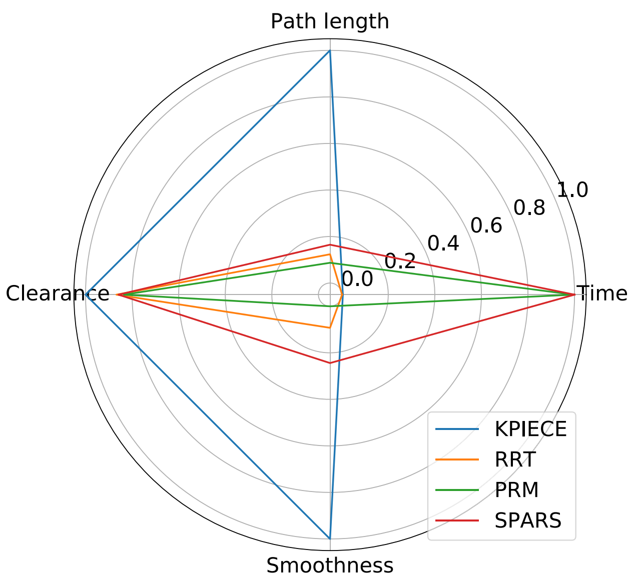


Fig. 7 Relative performance of planners in a static planning scene

Figure 7 presents a consolidated view of the relative performance of the planners across all proposed experiments. The data in this graph are expressed in percentage terms for each metric. There is a marked distinction in the metrics for the KPIECE planner, indicating its different performance profile. Conversely, the results garnered using the RRT, PRM, and SPARS planners exhibit similarity across all three experiments.

Table 1 details the results for the index of each planner. These results confirm that all planners successfully identified valid paths within the maximum allotted time for the queries in the proposed experiments. Focusing on the path length metric, the PRM planner achieved the shortest path, whereas the KPIECE planner resulted in the longest. In terms of this metric, the KPIECE planner exhibited a standard deviation of 61.95 cm, which is considerably higher compared to the other planners: PRM at 3.70 cm, RRT at 10.17 cm, and SPARS at 10.55 cm. Regarding the smoothness metric, which reflects the trajectory's level of smoothness executed by the planner, the PRM achieved the highest smoothness level. In contrast, the KPIECE planner demonstrated the lowest level of smoothness, as illustrated in Fig. 8.

Evaluating the performance of the planners using a static planning scene provides an approximation of the expected behavior of the planners. However, to obtain a real performance measurement it is necessary to perform the evaluation of the planners using dynamic planning scenes, that is, processing in real time of the different actors and objects that interact in the work environment. In the following section, an analysis of the environment perception techniques is presented, as well as an explanation of the ROS node for the computation of the different real-time performance metrics of the selected planner.

5.2 Dynamic obstacle collision

In the dynamic environment, two inputs were considered to build the planning scene: PointCloud and DepthMap. Both

Fig. 8 Average solution of trajectory smoothness achieved by the planners in a static planning scene

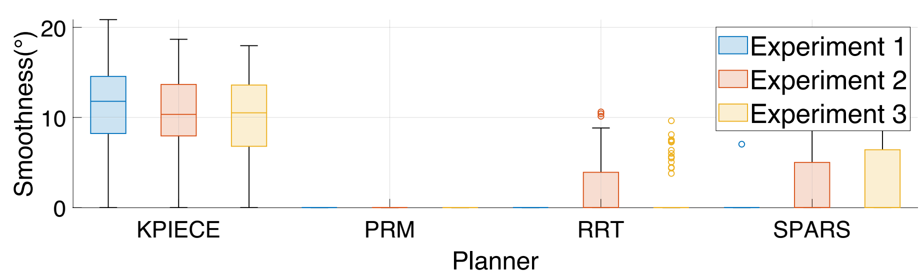
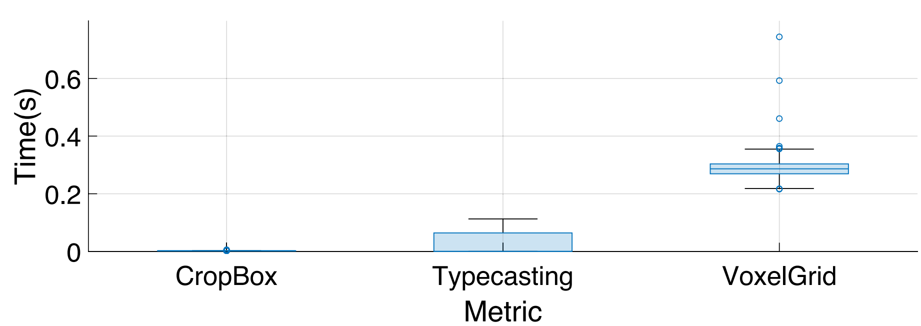
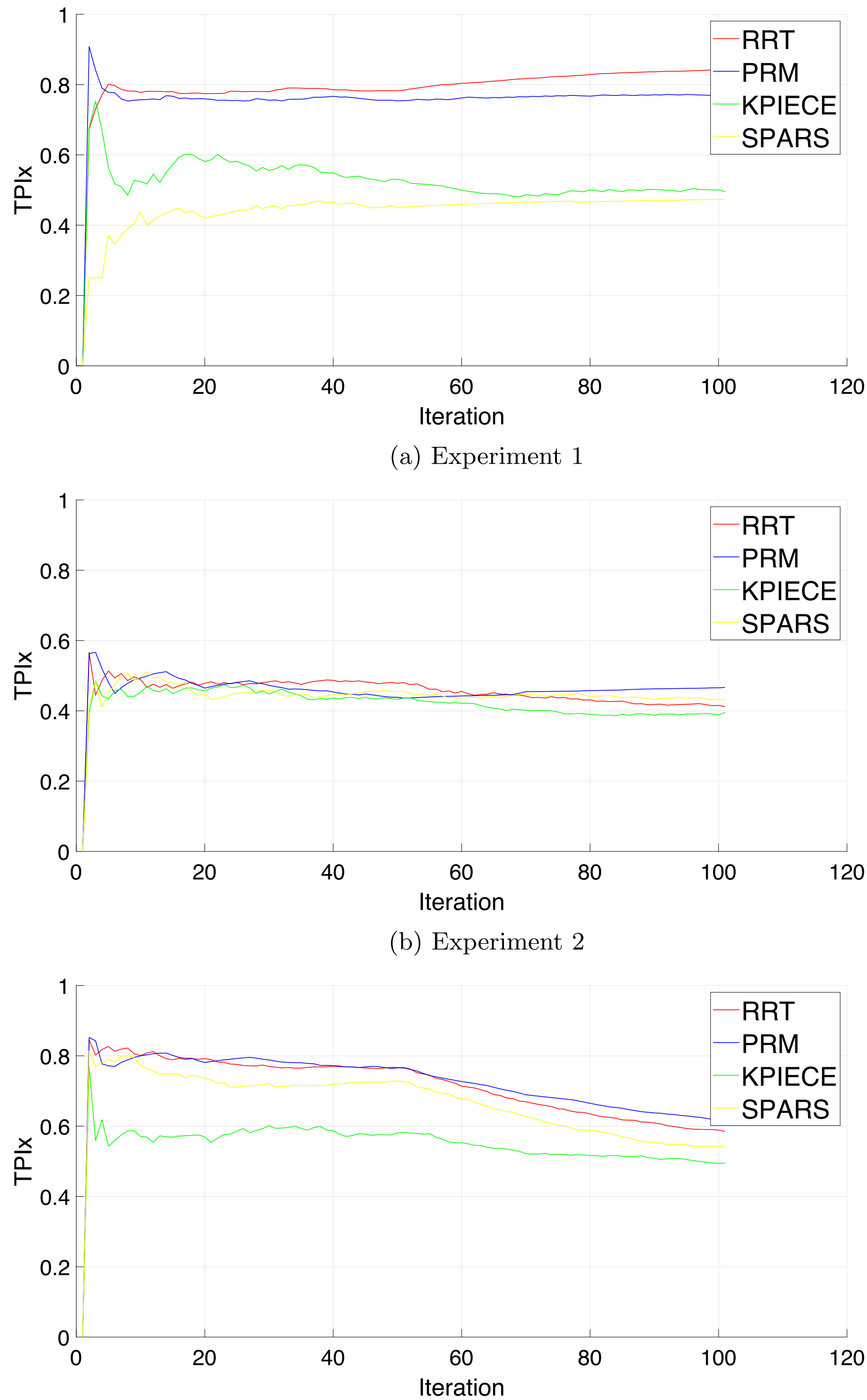


Fig. 9 PCL library processing time





(a) Experiment 1

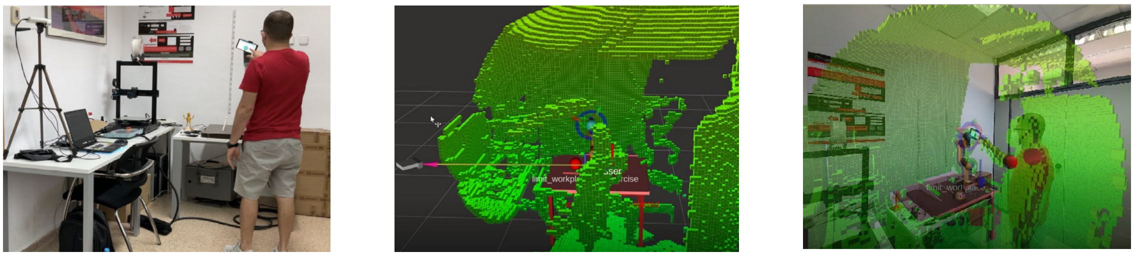
(b) Experiment 2

(c) Experiment 3

Fig. 10 Evaluation of TPIx for each experiment in a dynamic scene

data information were obtained from the RGB-D sensor, and used by MoveIt through the plugins PointCloudOctomapUpdater and DepthImageOctomapUpdater, respectively.

For the evaluation of the proposed rehabilitation system in the dynamic scene, the following processing times were considered:



(a) Color image (b) Occupancy map (c) Color image + Occupancy map

Fig. 11 Example occupancy map using as input DepthMap

- Processing time to generate the OctoMap using as inputs PointCloud or DepthMap.
- In the case of OctoMap generation using PointCloud, the processing time considered was evaluated considering the process of filtering, downsampling and segmentation.
- The time required for the real-time computation of the performance metrics for each planner.

Regarding the results obtained in the processing times, in the case of using the original PointCloud input generated by the RGB-D sensor and considering the proposed exercises, an average of 0.4 Hz was obtained when updating the planning scene monitor. When performing an optimization of the input PointCloud using the PCL library, a response time improvement of 0.7 Hz was obtained. Figure 9 shows the time required to execute the filtering, downsampling and typecasting of the PCL library, where applying the cropbox filter to the UR3 workspace requires an average of 2.05 ms, the typecasting required by PCL consumes an average of 32.43 ms and applying VoxelGrid downsampling requires an average of 286.65 ms.

Figure 10 shows the values of the TPIx calculated by the planner, considering the three proposed experiments. In each experiment, one hundred iterations were carried out. The graphs show that the RRT and PRM planners obtain a better TPIx during the experiments.

When using the DepthMap to generate the occupancy map required by the MoveGroup, a performance of 1.96 Hz was obtained, which is an adequate frequency for our proposed system. Figure 11 shows an example of the occupation map.

The evaluation ROS node provided in this study takes 2.11 ms to compute the performance metrics of the schedulers: path length, planning time, smoothness and clearance.

6 Conclusions and future works

This paper introduces a novel approach for the assessment of safe human–robot interaction by thoroughly analyzing and comparing four planning algorithms: KPIECE, PRM, RRT, and SPARS, all available through the OMPL and integrated within MoveIt. A new evaluation method, including the TPIx, has been developed to provide a comprehensive summary of various metrics such as planning time, path length, clearance, and path smoothness.

The experimental results in a static environment demonstrate that the PRM algorithm is the most effective for the proposed scenarios, followed by RRT, SPARS, and KPIECE. In dynamic environments, real-time generation of the occupancy map is crucial for trajectory planning and metrics computation. To facilitate this, a ROS node was developed that generates robot trajectories and computes the performance metrics of the planners in real-time, offering an advantage over MoveIt, which computes these metrics only in static scenarios.

The new evaluation method was successfully tested in collaborative environments where operator safety is paramount. The research proposes a real-time perception and planning system designed to prevent collisions between the robot and the operator or any object within the workspace. This system, comprising a collaborative robot and an RGB-D sensor, utilizes 3D data to monitor the environment and generate safe trajectories, while also evaluating the effectiveness of the planners in use. Basic reaching tasks involving upper limb movements were tested, and a mobile application was developed to guide the operator, setting targets at the end of the UR3 robot arm. This application was integrated into the main ROS node and is scalable for additional tasks. In summary, a new method for evaluating safe human–robot interaction has been established, and its effectiveness was demonstrated through extensive testing with various planning algorithms.

Future work will focus on enhancing the intelligent robotic system by implementing additional improvements to dynamically select the most suitable planner based on various work scenario configurations. This will be achieved by leveraging historical evaluation data of all metrics and TPIx. Furthermore, the research will incorporate user-centric evaluations to understand how different planners affect human–robot collaboration in practical settings, ensuring that the improvements align with real-world application needs and enhance overall effectiveness in collaborative environments.

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Author Contributions O.H. created the software tools necessary to implement the proposed system, recorded and analyzed the data, and wrote the manuscript. C.J., V.M. and A.U. reviewed and wrote the manuscript, designed the recording protocols, and validated the data.

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Data Availability No datasets were generated or analysed during the current study.

Code availability The authors declare that the data supporting the findings of this study are available within the paper, its supplementary information files and code derived from the research that can be used by other researchers is available in the repository: https://github.com/OHernandezr/huro_app_planner_metrics.

Declarations

Conflict of interest The authors declare no Conflict of interest.

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Consent to Participate Not applicable.

References

Brito, T., Lima, J., Costa, P., Piardi, L.: Dynamic collision avoidance system for a manipulator based on rgb-d data. In: Iberian Robotics Conference, pp. 643–654 (2017). Springer

Chitta, S.: Moveit!: an introduction. Stud. Comput. Intell. **625**, 3–27 (2016). https://doi.org/10.1007/978-3-319-26054-9_1/FIGURES/14

Dobson, A., Krontiris, A., Bekris, K.E.: Sparse roadmap spanners. In: Frazzoli, E., Lozano-Perez, T., Roy, N., Rus, D. (eds.) Algorithmic Foundations of Robotics X, pp. 279–296. Springer, Berlin, Heidelberg (2013)

Dumonteil, G., Manfredi, G., Devy, M., Confetti, A., Sidobre, D.: Reactive planning on a collaborative robot for industrial applications. In: 2015 12th International Conference on Informatics in Control, Automation and Robotics (ICINCO), vol. 2, pp. 450–457 (2015). IEEE

Hentout, A., Aouache, M., Maoudj, A., Akli, I.: Human-robot interaction in industrial collaborative robotics: a literature review of the decade 2008–2017. Adv. Robot. **33**(15–16), 764–799 (2019)

Hernández, Ó.G., Morell, V., Ramon, J.L., Garcia, G.J., Jara, C.A.: Rgbd data analysis for the evaluation of trajectory planning algorithms in human robot interaction environments for rehabilitation. In: Tardioli, D., Matellán, V., Heredia, G., Silva, M.F., Marques, L. (eds.) ROBOT2022: Fifth Iberian Robotics Conference, pp. 361–372. Springer, Cham (2023)

Kavraki, L.E., Svestka, P., Latombe, J.-C., Overmars, M.H.: Probabilistic roadmaps for path planning in high-dimensional configuration spaces. IEEE Trans Robot Autom **12**(4), 566–580 (1996). https://doi.org/10.1109/70.508439

Kuffner, J.J., LaValle, S.M.: Rrt-connect: an efficient approach to single-query path planning. In: Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065), vol. 2, pp. 995–1001. IEEE (2000)

Kumar, A., Bahubalendruni, M.V.A.R., Ashok, D.: Challenges and opportunities in human robot collaboration context of industry 4.0—a state of the art review **49**, 1–14 (2022). https://doi.org/10.1108/IR-04-2021-0077]

Mandischer, N., Gurtler, M., Weidemann, C., Hüsing, E., Bezrucav, S.-O., Gossen, D., Brünjes, V., Hüsing, M., Corves, B.: Toward adaptive human robot collaboration for the inclusion of people with disabilities in manual labor tasks. Electronics **12**(5) (2023). https://doi.org/10.3390/electronics12051118

Melchiorre, M., Scimmi, L.S., Mauro, S., Pastorelli, S.P.: Vision-based control architecture for human-robot hand-over applications. Asian J. Control **23**(1), 105–117 (2021). https://doi.org/10.1002/ASJC.2480

Meziane, R., Li, P., Otis, M.J.-D., Ezzaidi, H., Cardou, P.: Safer hybrid workspace using human-robot interaction while sharing production activities. In: 2014 IEEE International Symposium on Robotic and Sensors Environments (ROSE) Proceedings, pp. 37–42 (2014). https://doi.org/10.1109/ROSE.2014.6952980

Nikolakis, N., Maratos, V., Makris, S.: A cyber physical system (cps) approach for safe human-robot collaboration in a shared workplace. Robot. Comput. Integrat. Manufact. **56**, 233–243 (2019). https://doi.org/10.1016/j.rcim.2018.10.003

Olaronke, I., Oluwaseun, O., Rhoda, I.: State of the art: a study of human–robot interaction in healthcare. Int. J. Inform. Eng. Electron. Bus. **9**(3), 43–55 (2017). https://doi.org/10.5815/IJIEEB.2017.03.06

Planners, M.: MoveIt Planners. https://moveit.ros.org/documentation/planners/. Accessed: 2022-06-18

roslibjs - ROS Wiki. http://wiki.ros.org/roslibjs. Accessed: 2022-08-03

Rusu, R.B., Cousins, S.: 3D is here: Point Cloud Library (PCL). In: IEEE International Conference on Robotics and Automation (ICRA), pp. 1–4. IEEE, Shanghai, China (2011). https://doi.org/10.1109/ICRA.2011.5980567

Safeea, M., Neto, P.: Minimum distance calculation using laser scanner and imus for safe human-robot interaction. Robot. Comput. Integr. Manufact. **58**, 33–42 (2019). https://doi.org/10.1016/j.rcim.2019.01.008

Scimmi, L.S., Melchiorre, M., Troise, M., Mauro, S., Pastorelli, S.: A Practical and effective layout for a safe human-robot collaborative assembly task. Appl. Sci. **11**(4), 1763 (2021). https://doi.org/10.3390/APP11041763

Secil, S., Ozkan, M.: Minimum distance calculation using skeletal tracking for safe human-robot interaction. Robot. Comput. Integr.

Manufact. **73**, 102253 (2022). https://doi.org/10.1016/j.rcim.2021.102253
Şucan, I.A., Kavraki, L.E.: Kinodynamic motion planning by interior-exterior cell exploration. In: Algorithmic Foundation of Robotics VIII, pp. 449–464. Springer, Berlin (2009)
Şucan, I.A., Moll, M., Kavraki, L.E.: The Open Motion Planning Library. IEEE Robot. Automat. Mag. **19**(4), 72–82 (2012). https://doi.org/10.1109/MRA.2012.2205651. https://ompl.kavrakilab.org
Tsarouchi, P., Makris, S., Chryssolouris, G.: Human-robot interaction review and challenges on task planning and programming. Int. J. Comput. Integr. Manuf. **29**(8), 916–931 (2016). https://doi.org/10.1080/0951192X.2015.1130251
Uccheddu, F., Furferi, R., Governi, L., Carfagni, M.: Rgb-d-based method for measuring the angular range of hip and knee joints during home care rehabilitation. Sensors **22**(1) (2022). https://doi.org/10.3390/s22010184
Universal Robots-User manual - UR3 CB-Series - SW3.3 - English international. https://www.universal-robots.com/download/manuals-cb-series/user/ur3/33/user-manual-ur3-cb-series-sw33-english-international/. Accessed: 2022-08-03
Zhang, J., Li, P., Zhu, T., Zhang, W.-A., Liu, S.: Human motion capture based on kinect and imus and its application to human-robot collaboration. In: 2020 5th International Conference on Advanced Robotics and Mechatronics (ICARM), pp. 392–397 (2020). https://doi.org/10.1109/ICARM49381.2020.9195342

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