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# Behavioral Planning Approaches To Improve Autonomous Behaviour During Navigation for Mobile Robots Running ROS

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# Abstract

This thesis explores ways to improve the autonomy of mobile robots running the Robot Operating System (ROS) with behavioral planning approaches. Autonomous mobile robots often require close human supervision or intervention during their operation. A system supervision system, a sensor data storage and a behavior tree were designed and implemented. The system was tested on a simulated robot in the Gazebo simulator. Behaviors to handle sensor failures, collisions, unreachable goals, and low battery state were implemented with a behavior tree. The different test scenarios were artificially induced in a standardized manner to trigger the behaviors to react to the scenarios. The results show an increase in the robot's autonomy and robustness to failures. The results need to be tested and verified on a real robot, but the increase in the robot's autonomy in the simulation tests are promising an equally positive result. Behavior trees to control and improve the behavior of robots offer the ability to effortlessly add new behaviors to an existing system. This thesis shows a comprehensive way how behavior trees can be implemented to an existing ROS2 system.

# Chapter 1

# Introduction

Mobile robots are becoming more widespread in many domains, like warehouse logistics, last-mile delivery, and agriculture. They are marketed as autonomous mobile robots, but their autonomy is often limited to particular environments and requires frequent human help to function correctly. This reliance on a human operator hardly qualifies the robot to be labeled autonomous.

One of the quickest and most popular ways to build and program a robot is to use the Robot Operating System (ROS). ROS offers many tools and functionalities to create and program robots, but a standard robot needs human supervision during the operation to ensure proper function and safety. The robot needs to be able to navigate in an uncertain environment to guarantee the safety of the robot itself and all other actors in its environment. There are ROS packages to enable safe navigation capabilities, but currently, typical ROS-based robots cannot react to unforeseen events.

In theory, the robot can perform fully autonomous navigation, including mapping and localization. However, the robot's autonomy can not be guaranteed when something unexpected happens. A default robot cannot represent all possible fail states and does not detect failures on a systematic level but only inside its navigation-related subsystems. Moreover, when failures inside these subsystems are discovered, the options to handle these problems are minimal and often do not deal with the problems in an autonomous way. The reliance on external problem-solving decreases the robot's usefulness when tasked with tangible goals. Therefore, this thesis centers around the research question of how behavior planning can increase the robustness and autonomy of a robot running ROS2. Behavior planning enables the robot to react to failures and problems of the system and can decide alternative courses of action to mitigate risks and finish the given tasks.

This thesis will explore possibilities for improving current systems by adding a dedicated behavior planning component. Furthermore, the thesis seeks to provide an im-

plementation of exemplary behaviors and a system architecture to incorporate behavior planning in other robots.

The desired outcomes of this implemented software will be an increase in robustness and a decrease in required human actions during several scenarios. In these scenarios, failures and problems will be artificially induced to test the robot's abilities to behave autonomously.

The remainder of this thesis is organized as follows:

- Chapter 2 presents the state of the art and compares the different behavior planning approaches
- Chapter 3 analyzes the current robotic systems and derives requirements from the critical problem areas
- Chapter 4 describes the implemented software approach, including the overall system architecture
- Chapter 5 shows the obtained results from all selected scenarios and discusses the acceptance criteria of the requirements
- Chapter 6 summarizes the thesis novelty by showing how the implemented approach answers the research question
- Chapter 7 provides an outlook of future work and recommendations

# Chapter 2

# State of the Art

## 2.1 Automated and Autonomous Vehicles

This thesis aims to increase the autonomy of mobile robots. In order to define an improvement in autonomous behavior, one needs to explore the definitions of the terms "automated" and "autonomy". The "Expertenkommission Forschung und Innovation" (EFI) defines the term autonomy in the context of robotics as a system that can act without human instructions and still solve complex tasks, make decisions, learn independently as well as react to unforeseen circumstances [1]. The definition specifies the needed requirements to make a robot fully autonomous.

The Society of Automotive Engineers (SAE) defines vehicle autonomy based on the human driver's need for supervision and possible intervention when executing complex driving tasks [2]. Figure 2.1 on page 5 depicts the different levels of autonomy of passenger cars on a scale between no automation to completely autonomous. The most significant distinction between the levels is between levels two and three because a system can take complete control over the vehicle in certain conditions. The SAE levels zero to two use driver support functions with no autonomy, while levels three to five employ automated driving features. Another major level difference is located on the borderline between levels three and four as the vehicle can drive autonomously without a human operator who could control the vehicle as a safety fallback when the system demands it. A level four vehicle can theoretically be built without a steering wheel and pedals because it can handle all situations it is deployed in without requiring manual driving.

Both definitions rely on human supervision and guidance as the central part of what hinders a system or vehicle from becoming fully autonomous. By decreasing the instances of human intervention during the operation of a robot, one can increase the automation level towards full autonomy. However, this has to be done by equipping the robot with

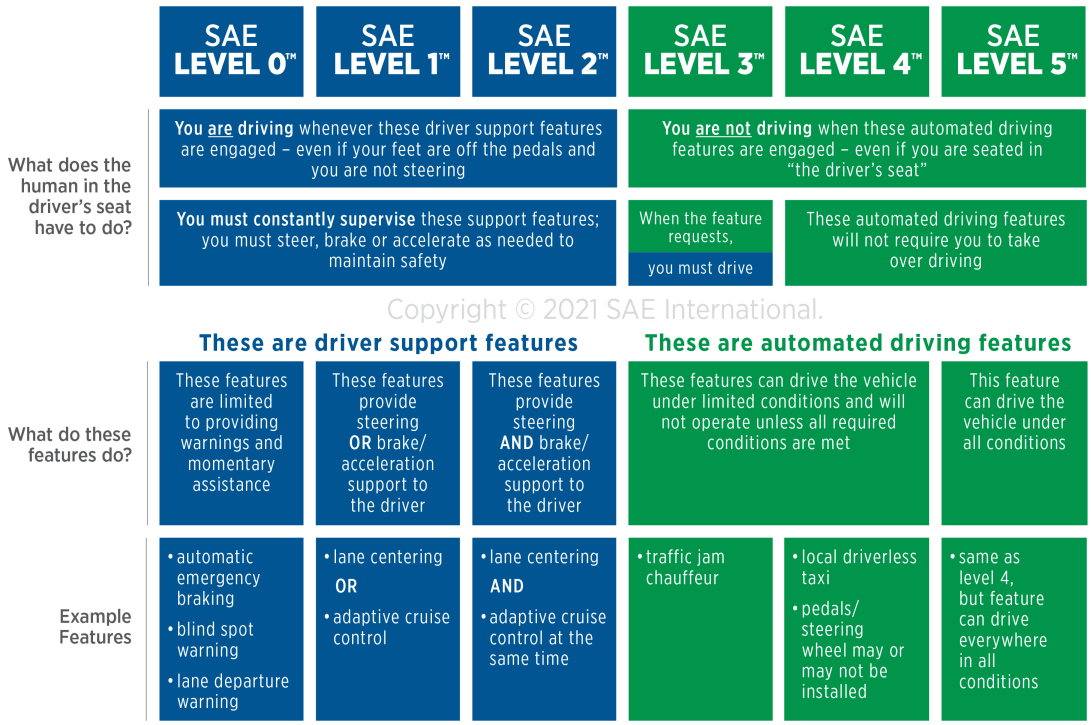



Figure 2.1: Levels Of Driving Automation [2]

robust and context-driven decision-making and planning capabilities. Otherwise, a robot that never needs a human to operate could easily be created. Nevertheless, this robot could not be considered autonomous as it would not be able to solve complex tasks and make intelligent decisions.

## 2.2 Autonomous Driving Navigation Architectures

To better understand how behavior planning influences a robot's autonomy, one can look at the latest and most used software architectures for autonomous driving on a functional level. The majority of the current autonomous driving architectures implement a hierarchical structure that follows the "*Sense - Think - Act*" paradigm [3].

As shown in figure 2.2 (p. 6), the sensory inputs, usually from multiple sensors, are processed to create an environment representation. Based on that representation, the system calculates how to get from its current position to the destination and creates a path to the destination. A second planning calculation is triggered to compute the motion commands while considering the system's constraints (e.g., size, turning radius). In a final step, these motion commands then get converted to control the motors.

The planning sequence can be further divided into "*global*", "*behavioral*", and "*local*"

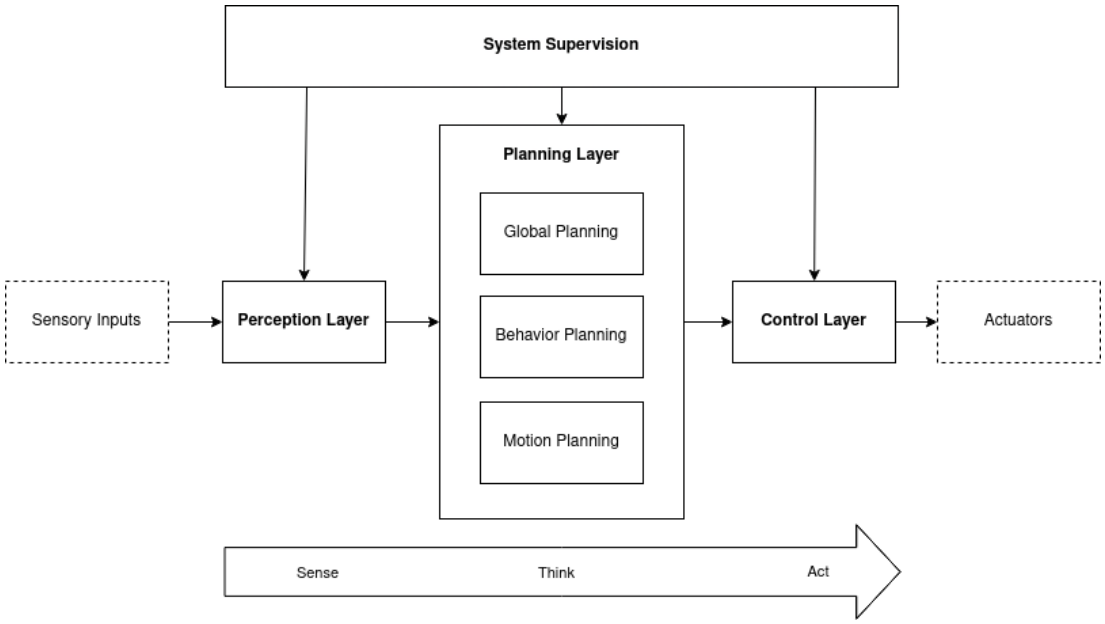



Figure 2.2: Common Autonomous Driving Architecture [4, 5]

planning. The global planning module, also named "*route planning*", is responsible for outputting a path from start to goal. Global planning is comparable to a person using Google Maps to find the shortest or fastest path to a faraway city. In this analogy, the behavior planner is responsible for following the traffic rules on the trip to the destination, e.g., stopping at red lights, giving the right of way to other vehicles, and following speed limits. The local planning, also named motion planning, takes the input from the behavior layer and is tasked to let the vehicle drive according to the executed behavior so that it stays in its lane and stops at a red light at the correct position [6].

Due to safety considerations, many autonomous driving architectures implement an additional system supervision layer that monitors the execution of the other system components. This supervisor checks the health of all software components. If one or more components fail to pass the health check, the supervisor is responsible for ensuring that the system does not continue the regular driving routine. The supervision component triggers measures to restore the standard functionality or, if that is not possible, bring the robot into a safe state [7].

Considering that with these architectures, vehicles can achieve an SAE level of autonomy up to level four and even five [8], a good starting point to increase autonomy in a robotic system would be to ensure that all of the functional modules in figure 2.2 are implemented and available. Higher autonomy levels are achievable by expanding the behavior planning module inside the planning layer.

## 2.3 Behavior Types

The behavior planning module contains a set of tailored behaviors to operate in a specific environment. The module's task is always to choose the best behavior to execute to ensure the best performance for a given task. In this sense, behavior is defined as a mapping of sensory inputs to a pattern of actions that carry out a specific task [3]. A good behavior planning approach provides the robot with acceptable behaviors for every possible scenario the robot is operating in. Different scenarios pose challenges for the behavior planning module, which has to decide on the best behavioral option to achieve a higher-level goal.

### 2.3.1 Reactive

During the emergence of behavior-based robots in the 1960s, the first type of behaviors implemented were simple reactive behaviors. This behavior type maps a sensory input directly to motor commands. In human behavior, this behavior resembles reflexes, like tapping on the kneecap, which unwillingly results in motion in the knee joint. This behavior pattern is not following the typical "Sense, Think, Act" loop but shortcuts directly from sensing to acting [9]. Reactive behaviors can be chained together to achieve more advanced and goal-driven behaviors.

Despite the possibility of carrying out more complex robot behaviors, sequential behaviors remain primarily on the level of reactive behaviors due to the lack of a planning and decision-making cycle during their execution. The computational load of reactive behaviors is low and therefore fast as no decision and planning process is taking place, which makes them suited in scenarios where real-time safety is of concern. This property makes this behavior type useful for system supervisors, where immediate reactions with low latency are sometimes required to ensure system safety.

However, a system with a solely reactive behavior planning approach will always fail to meet the requirements for higher levels of autonomy due to the reasons discussed in previous chapters. This systematic lack of autonomy does not mean reactive behaviors can not be part of highly autonomous systems. The quick response time to sensor inputs makes them valuable in improving vehicle safety and reliability.

### 2.3.2 Deliberative

Systems purely based on reactive behaviors suffer the drawback that they do not allow for complex behaviors. In addition, creating sequences of reactive behaviors that produce the target behavior is a complicated task [3]. Behaviors that involve planning and

decision-making aspects are defined as deliberative. Unlike reactive behaviors, deliberative behaviors follow the "*Sense - Think - Act*" paradigm, and they are not mapping sensory inputs directly into motor commands. Instead, deliberative-type behaviors can decide the best course of action before they act. Using deliberative behaviors inside the planning module enables a robot to meet the definition of autonomy, especially in making decisions and reacting to unforeseen circumstances.

A behavior planner with a deliberative approach can make decisions based on current sensor data and previously processed data. The deliberative behavior planner can predict environmental changes by incorporating older sensor information into the decision-making process. Using older data points allows the planner to proactively adapt the motion planning commands to better achieve goals in dynamic and uncertain environments.

For example, a motion prediction of obstacles in highly dynamic environments would improve motion planning considerably. The behavior planner can adjust the motion planning with more precise information on how dynamic obstacles interact with the robot's planned path in the future. A purely reactive planner could never determine if an obstacle is destined to intersect the robot's path in the future and would constantly reroute to accomplish the given goal.

On the other hand, a deliberative planner can determine if the best course of action is to stay on the current path as the dynamic obstacle has already moved away by the time the robot reaches the intersection point. Other actions in the scenario are possibly slowing down or speeding up briefly to avoid an obstacle and staying on the current path, which is calculated to be quicker than rerouting and taking a longer path.

Concluding, the focus should be on creating deliberative behaviors to improve autonomy. Generally, these cognitively more complex behaviors mimic human skills and thus make a system more autonomous because the need for a human operator can be significantly decreased.

### 2.3.3 Hybrid

One can combine reactive and deliberative behaviors in a hybrid model to create reliable and intelligent systems. This behavior planning module can quickly react to incoming sensor data and still exhibit high levels of automation.

Figure 2.3 (p. 9) shows the areas where reactive and deliberative behaviors have advantages and limitations. Deliberative planning does possess limitations during the execution of generated plans as the time horizon is long-term and not able to react to fast changes in the environment. When the system is not addressing these points, deliberative robots focus on a narrow problem domain and are not robust when the defined system

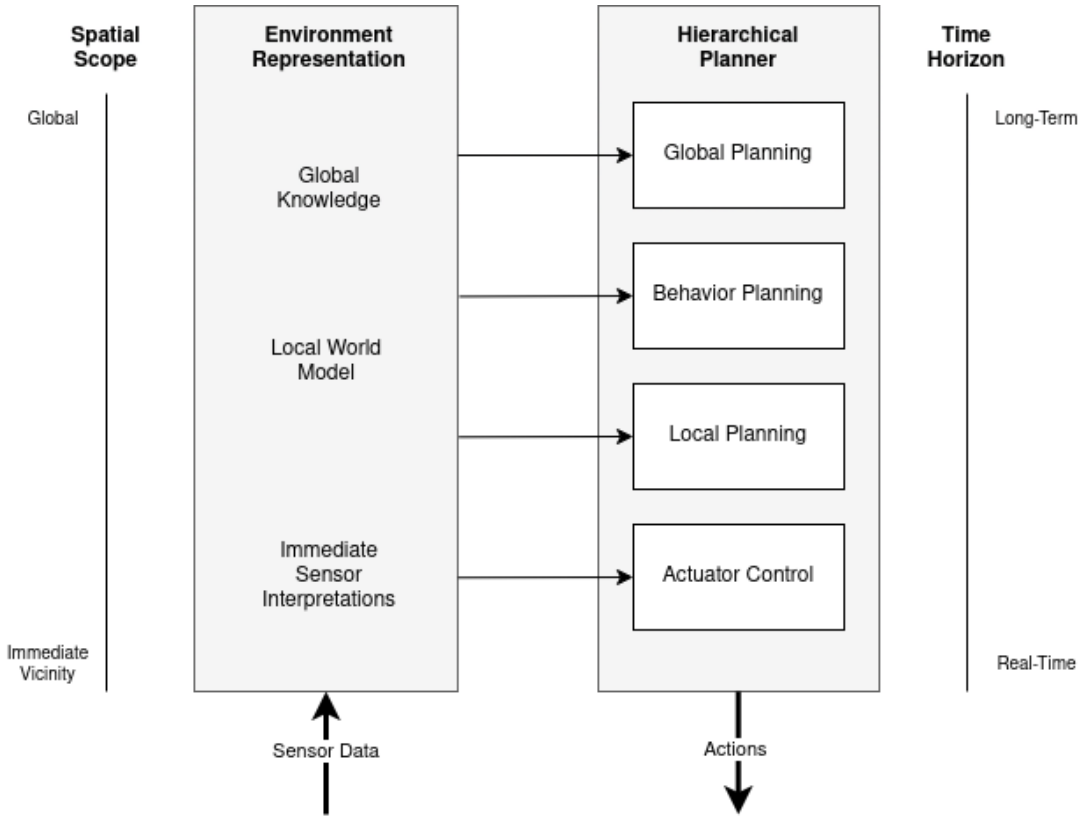



Figure 2.3: Hybrid Planning Architecture [10]

boundaries are crossed[10].

The incorporation of reactive behaviors into behavior planning combats this problem. In this multi-layer approach, the higher level, more deliberative planners can override the reactive planners to allow the system to be more flexible in uncertain environments and adaptable while maintaining fast reaction times. This architecture leads to more robust robots deployed in a wider variety of environments, thus leading to higher levels of autonomy.

## 2.4 Behavior Planning Approaches

Robots that use a hybrid, hierarchical behavior planning approach need a system that decides on a high level which behaviors are executed. That system allows overriding simple reactive behaviors with more complex, deliberative behaviors when the whole system benefits from them.

The solutions for behavior execution systems, presented in the following sections, all share the usage of states that a robot can be in. Different strategies and behaviors are

utilized during the system's runtime based on a robot's state and additional information about the environment.

In the following sections, different approaches for behavior planning are presented and compared.

### 2.4.1 Finite State Machines

Finite State Machines (FSM) are commonly used in the autonomous driving domain. They describe behavior in the form of states, which trigger the execution of actions. A finite state machine is defined by a list of possible states , a starting state $s_0$, a set of state transitions $\delta$, a set of final states $F$, and the input alphabet $\sigma$. At any given time, only a single state is selected, and its containing actions are executed.

Figure 2.4 depicts an example state machine with different states and exemplary transitions between them. Inside of the states the letters indicate the existence of actions. $E$ stands for entry, $I$ for Input and $X$ for Exit. The arrows between the states illustrate the possible transition and transition conditions for every state. A state transition diagram is an excellent way to understand the system behavior, but it can not show the details of the modeled behavior, like the actions [11].

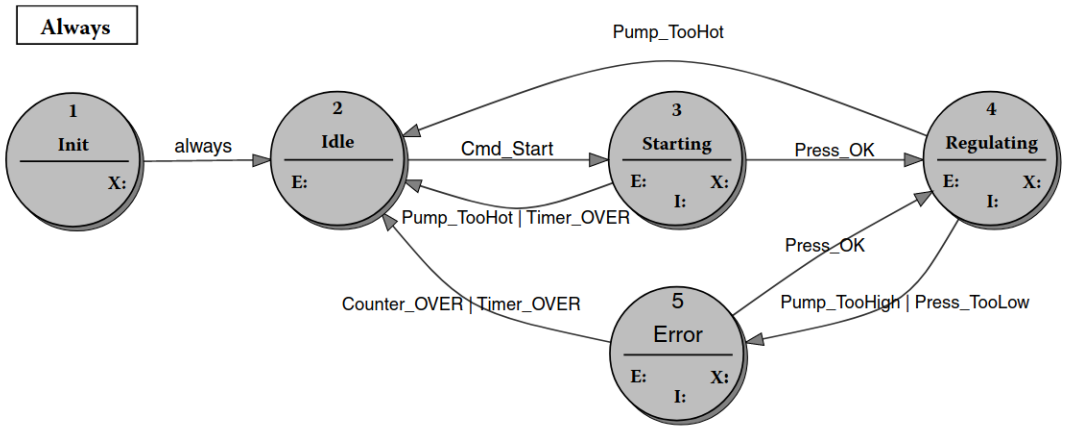



Figure 2.4: Example of a finite state machine transition diagram [11]

The execution time of finite state machines can be fast enough to control the motors of a bipedal robot to enable the robot to balance and walk despite unexpected height variations between steps [12]. The high performance makes state machines very well suited for fast, reactive type behaviors while allowing a deliberative and hierarchical approach to behavior planning.

Creating small state machines can be accomplished easily and quickly using various feature-rich, and performant libraries [13]. Finite state machines are often used to compre-

hensively model reactive and sequential behaviors in autonomous driving functions [14]. These finite state machines use nested state machines inside another state machine. The nested state machines reduce the complexity of the state machine as the transitions do not need to be modeled because a nested state machine's start and final state are treated as just one state inside the bigger state machine.

Despite the possibility of nesting state machines, the effort to expand and maintain a FSM multiplies rapidly when the system becomes increasingly larger to integrate more complex behaviors. The higher effort is due to the required creation of the transitions, transition conditions, and transition events. The FSM needs to be updated with each new state introduced into the state machine as existing states need to be checked and corrected accordingly [15].

### 2.4.2 Behavior Trees

Behavior Trees (BT) are another way to model and control the behavior of autonomous systems. Behavior Trees first found considerable acceptance in the computer game industry, where they are mainly used to model artificial intelligence for non-player characters [16]. Every tree has one root and many children, parent, and leaf nodes. Leaf nodes are also called execution or action nodes, while non-leaf nodes are control or control flow nodes.

Table 2.1: The five types of behavior tree nodes [17]

| **Node type** | **Symbol** | **Succeeds** | **Fails** | **Running** |
|---|---|---|---|---|
| Sequence | -> | If all children succeed | If one child fails | If one child returns running |
| Fallback | ? | If one child succeeds | If all children fail | If one child returns running |
| Parallel | -> -> | If >= M children succeed | If > N-M children fail | else |
| Action | shaded box | Upon completion | If impossible to complete | If node is still completing tasks |
| Condition | white oval | If true | If false | Never |

The execution of a behavior tree is done by ticking the tree's root node. This signal then travels down to the child node of the root node, where either control nodes are ticked, or

action nodes are executed. Nodes return either "Success", "Running" or "Failure" which influences how the tick signal gets processed by the rest of the behavior tree.

The relevant control nodes are of the type "Sequence", "Fallback" or "Condition". The condition node can not have child nodes and can only return success or failure. A sequence node can be compared to a logical "and" condition. This property of the sequence node means that once a sequence gets ticked from the parent node, it will send the tick signal to every child node as long as they return "Success" or "Running" and only return "Success" itself when every child node was successfully ticked. If any children nodes return "Failure", the sequence node will stop ticking the remaining children and return "Failure".

On the other hand, the fallback node is an equivalent of a logical "Or" condition. The fallback node ticks its children nodes as long as they return "Failure" or "Running" and will return "Success" if one of the ticked nodes returned "Success". It will only return "Failure" if all children nodes returned "Failure". The primary node types and their control flow modification are listed in table 2.1 (p. 11). Parallel control nodes are listed for completeness but are not discussed further in this chapter due to their limited use in robotic applications.

Figure 2.5 depicts an example of a BT with multiple levels and action nodes. The nodes with the arrow (->) symbol are sequence nodes, and the question mark (?) symbol denotes fallback nodes. The condition nodes are depicted as white ovals, and the action nodes are represented as gray rectangles in the behavior tree example.

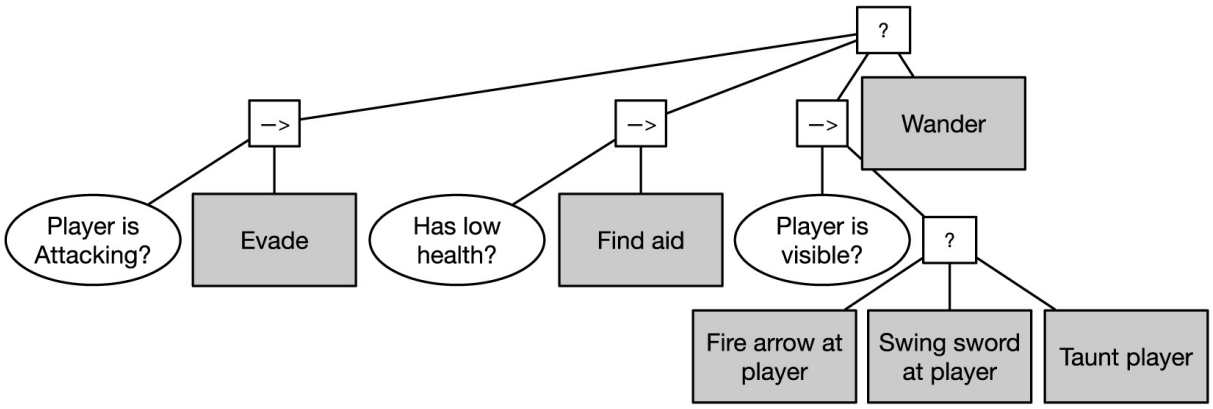



Figure 2.5: Example of a behavior tree [17]

One of the core differences to the Finite State Machine is that transitions between states are not distributed across all the states. In contrast, they are organized in a hierarchical tree, where the leaves represent the states [17]. FSM and BT can produce the same behavior in robots. However, the fundamental shift in how the two systems are created leads to significant advantages in the modularity, synthesis, and analysis of the systems

at hand. These effects are more significant with an increase in the size of the system. Behavior trees offer much more flexibility when creating an advanced behavior layer for an autonomous system.

### 2.4.3 Partially Observable Markov Decision Processes

Another approach to behavior planning is the Markov Decision Process (MDP) and the further advanced Partially Observable Markov Decision Process (POMDPs). MDPs share structural features with Finite State Machines, but the behavior planning and state transitions are stochastic and not deterministic in contrast to FSMs. An MDP can be described as a tuple $< S, D, A, T, R >$. Like a finite state machine, the MDP has a set of possible states $S$ and a set of possible transitions $T$ between them. The transitions contain a probability of execution and must add up to 1.0 for each associated state. An MDP adds a set of finite actions $A$ and rewards $R$ to the system. Additionally, MDPs possess a set of discrete time steps, in this context often called epochs, $D$, which can be infinitely long. The guiding principle of MDPs is to maximize the expected reward by deciding on the best action. This policy $\pi$ is what guides the behavior of the MDP [18].

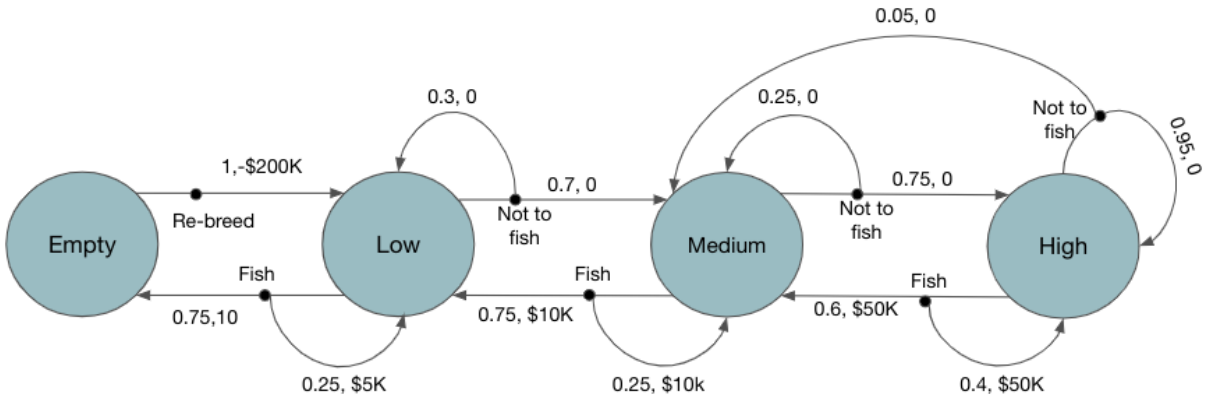



Figure 2.6: Example of a fully observable Markov Decision Process [19, 20]

Figure 2.6 shows an exemplary MDP for determining a fisherman's best course of action. The states are the population sizes of available fish, and the only available actions are to either fish or not to fish. The actions possess different rewards depending on the current state of the system [21].

The difference between an MDP and a POMDP is that in a POMDP, the system's current state can be unknown, and the system can make observations and estimate the state to a degree. The POMDP is defined as a tuple $< S, D, A, T, R, Z, O >$ in which the MDP tuple gets extended by $Z$ and $O$. $Z$ is the observation, and $O$ is the probability function of seeing $Z$ in a given state $S$.

POMDPs are well suited for applications in unknown environments because the system can make decisions if the perception information is imperfect or the environment is not fully observable. The decision process is probabilistic and is more adaptable when confronted with unknown scenarios. This flexibility comes at the cost of determinism. The system's behavior is not guaranteed to be the same whenever it is subjected to the same sensory input [22].

# Chapter 3

# Concept

This chapter presents the current state of mobile navigation with ROS and its limitations. This chapter aims to identify the critical areas in which standard mobile robots running ROS lack robustness and autonomy during autonomous mobile navigation. According to these critical areas, requirements are derived and prioritized with a risk analysis. This chapter proposes how behavior planning can improve the current default systems to meet the respective requirements.

## 3.1 Current State

### 3.1.1 ROS

The Robot Operating System (ROS) is an open-source middleware for creating robot applications. It is not an operating system (OS) since it needs an underlying OS, most commonly Linux, to work. ROS can handle the communication between different programs (called nodes) with standardized interfaces and network protocols. Nodes can communicate via topics, services, and actions, which differ in their application domain (compare table 3.1).

Table 3.1: ROS Communication Options

| **Name** | **Communication Pattern** | **Area of Use** | **Cardinality** |
|---|---|---|---|
| Topics | Publisher / Subscriber | Continuous stream of data (e.g. sensor data) | n:m |
| Services | Request / Response | Get specific data only once | One service, many clients |
| Actions | Request / Response and Publish / Subscribe | Trigger executing of asynchronous goal-driven processes and receive updates | One action, many clients |

This design choice makes robotic applications built with ROS highly reusable and interchangeable, allowing developers to integrate foreign libraries more easily into their applications. Due to the availability of many high-quality open-source libraries for many different use cases, ROS has become the leading methodology for creating robotic applications in the research environment [23].

With ROS2, the framework received fundamental changes and updates to its architecture and design to gain more acceptance and increased usage in the industry. These changes allow for real-time safety, simpler certification, and security when building industrial applications and products using ROS2 [24].

### 3.1.2 Turtlebot3

The Turtlebot3 is a standard mobile research platform with an available ROS interface to control the robot. The robot is well-integrated into the ROS ecosystem and is established in the literature as a system to develop and integrate new methods. The robot has two motors with attached wheel encoders to drive and steer, classifying it as a differential drive robot. A third omnidirectional wheel stabilizes the robot.

The manufacturer provides an open-source model for simulating the robot in physics-based simulators like Gazebo, as depicted in figure 3.1, which enables faster development and testing of the created robotic applications.

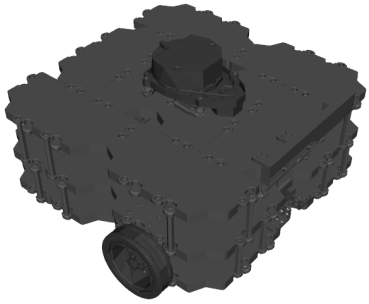


Figure 3.1: Turtlebot3 model in Gazebo simulator

The equipped sensors and easy simulation capabilities make the robot well-suited for using the Navigation2 stack and further development for behavior planning. The robot specifications are specified in table 3.2 (p.17). The turtlebot will be used to analyze the current state of mobile navigation. Furthermore, the simulated turtlebot will be the platform where the behavior planning will be implemented and tested.

Table 3.2: Turtlebot3 Specifications

| **Specification** | **Value** |
|---|---|
| Maximum translational velocity | 0.26 m/s |
| Maximum rotational velocity | 1.82 rad/s (104.27 deg/s) |
| Size (L x W x H) | 281mm x 306mm x 141mm |
| Singe Board Computer | Raspberry Pi (3 or 4) |
| Laser Distance Sensor (Lidar) | 360 Degree Laser Distance Sensor LDS-01 |
| Inertial Measurement Unit (IMU) | Gyroscope 3 Axis, Accelerometer 3 Axis |
| Actuators | XM430-W210 |

### 3.1.3 Navigation2

The ROS Navigation2 Stack (Nav2) combines different packages that allow mobile robots to navigate from point A to point B. Navigation2 is the de-facto standard for mobile navigation with a wide range of supported robots. Supported robot types are holonomic, differential-drive, legged, and ackerman (car-like). For the mobile robot to make use of the Nav2 stack, it has to be set up in a certain way to be able to generate plans and execute commands in the right way. The Nav2 setup requires the mobile robot to possess a laser scan or point cloud sensor, an odometry source (such as an Inertial Measurement Unit (IMU) or wheel encoders), a map with information about free and occupied spaces (Occupancy Grid Map (OGM)), and a set of transformations for planning and navigation (see figure 3.2).

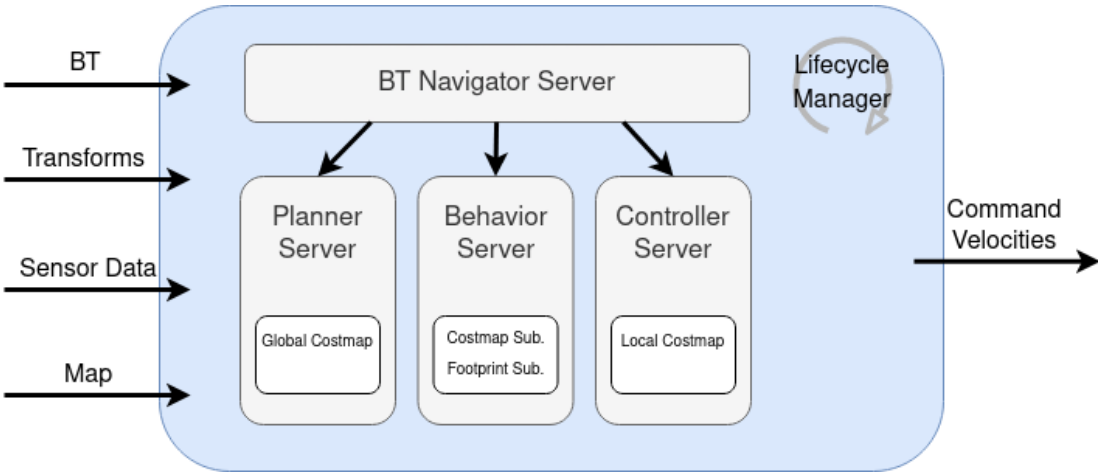



Figure 3.2: Navigation2 Architecture [25]

The stack contains tools that save and load occupancy maps, localize the robot, plan

paths, execute the path, provide cost maps, build behaviors, and execute recoveries [25]. These packages are often integrating a Simultaneous Localization and Mapping (SLAM) method to build or enlarge maps. Path planning and execution capabilities, which correspond to the global and local planner described in section 2.2, are further supported by ready-to-use planning plugins that use A* and Dijkstra algorithms for global path planning and a dynamic window approach for path execution (local planning). The system sequencing is done in a hierarchical structure as a central behavior tree calls asynchronous actions from the respective planners after another, as seen in figure 3.2 on page 17.

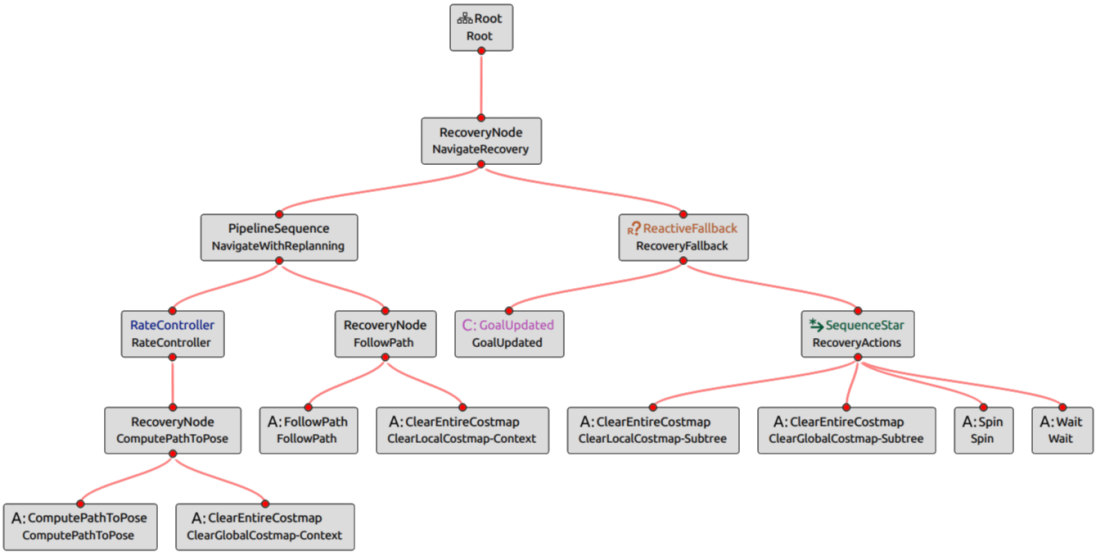



Figure 3.3: Navigation2 Behavior Tree

The behavior tree depicted in figure 3.3 is the default Nav2 behavior and has a set of recovery behaviors already implemented (spin, wait, back up, clear map). These behaviors are executed if the robot can not progress towards the set goal. Nav2 uses a node lifecycle management system to start, activate, deactivate, and shut down nodes in a controlled way. The lifecycle approach allows the system to monitor the system nodes' startups, executions, and failures.

With this quantity of functions and hierarchical architecture, the ROS Navigation2 stack is an excellent basis for achieving high levels of robot autonomy. The software can be modified and expanded with plugins to fit the users' needs. When comparing the functionalities of the software stack to the proposed autonomous system architecture in figure 2.2, the functionalities that Navigation2 is missing are a system-wide supervision layer and a more deliberative approach to behavior planning (as mentioned in section 2.3).

The absence of these components leads to a limited set of circumstances in which the robot can perform navigation reliably. One of the core problems behavior-based robots face

is generating a dependable environment representation. An accurate representation is the basis for the last steps in the planning part of the *"Sense - Think - Act"* cycle. Unforeseen events can severely limit the reliability of the environment representation without the robot detecting the unreliability.

Examples of such events currently not handled appropriately are slipping wheels, orientation changes by external influences, or undetected, more specifically, undetectable obstacles. These events can lead to erratic movement of the robot, as reactive behaviors and more deliberative behaviors compete for authority over the robot's movement. By design, to allow more intelligent robot behaviors, the deliberative behavior can override commands from reactive behaviors. However, the deliberative behavior's planning is based upon a false representation of reality, leading to incorrect commands.

The unsafe planning triggers reactive-type behaviors again to counteract the commands from the deliberative behavior. In a more severe scenario, the reactive behaviors may not get activated, and the robot continues to drive despite the incorrect interpretation of the surroundings. This highly unsafe behavior requires a human operator to step in and restore the robot manually to full functionality.

## 3.2 Requirements

The software requirements that improve the robot's behavior are derived from the current limitations of the standard ROS and Navigation2 setup for mobile robots described in the previous section. The non-functional requirements and descriptions are listed in table 3.3. The functional requirements and their acceptance criteria are listed afterwards in table 3.4 on page 20. Figure 3.4 on page 21 depicts a Use-Case diagram with the functions needed to improve the system's autonomy and better contextualize the system's requirements.

Table 3.3: Non-Functional Requirements

| **Nr.** | **Name** | **Priority** | **Description/Acceptance criteria** |
|---|---|---|---|
| non_freq1 | Single Point of Failure | High | The system does not have a single point of failure When parts of the system fail, the system maintains operability to a degree. |
| non_freq2 | Performance | High | The system's control loop guarantees fast reactions. The average frequency with which the system operates is higher than 100Hz (10ms). |
| non_freq3 | Determinism | High | The outcome for a given set of inputs must be deterministic, meaning that the behavior is always executed similarly. |
| non_freq4 | Deliberate | High | The robot can execute deliberative behaviors, meaning that behaviors new implemented behaviors go beyond reacting to sensor input and have a planning aspect. |

Table 3.4: Functional Requirements

| Nr. | Name | Priority | Description/Acceptance Criteria |
|---|---|---|---|
| fn_req1 | Sensor Failure | High | The system detects sensor failure. Ensure that the system can restart sensors and decrease the speed during the time the sensor delivers limited information. |
| fn_req2 | Emergency Detection | High | The system detects emergency. Ensure that the system can detect when the continuation on the calculated path is no longer safe (sensor failures, blockage). |
| fn_req3 | Emergency Stop | High | The system can initiate emergency stops. Ensure that the system can override all commands and stop in case an emergency is detected. |
| fn_req4 | Override Navigation2 | High | The system can override navigation2. Ensure that the system's commands can always override the commands coming from navigation2. |
| fn_req5 | Maintain operability | High | The robot executes commands as long as it is safe. Ensure that the robot keeps driving if it is safe even when system functions are not working correctly. |
| fn_req6 | Recovery | High | The system can recover from crashes. Ensure that the system can successfully reach goals despite previous crashes. |
| fn_req7 | Control Path Planning | Medium | The system controls and rates the quality of the planned paths. |
| fn_req8 | Reset Goals | Medium | The system can reset and override goals set by the user so that the goal is reachable by planners. |
| fn_req9 | Robot Range | Medium | Ensure that the robot will not run out of battery during navigation to a goal. |

The prioritization is based on the severity of the consequences for the system. The functional requirements one to six focus on safety and robustness of the robot and are therefore prioritized high. Functional requirements seven to nine focus on extending the autonomy of the robot, but a failure in these requirements do not pose as high of a risk the other requirements.

## 3.3 System Solution

For a Turtlebot3 running Nav2 to appropriately deal with the listed requirements, the system needs to be extended with new external modules. To eliminate a single point of failure for the system, one needs to create an independent second system outside the existing one. This aims to create a robust fallback behavior that does not rely on Nav2

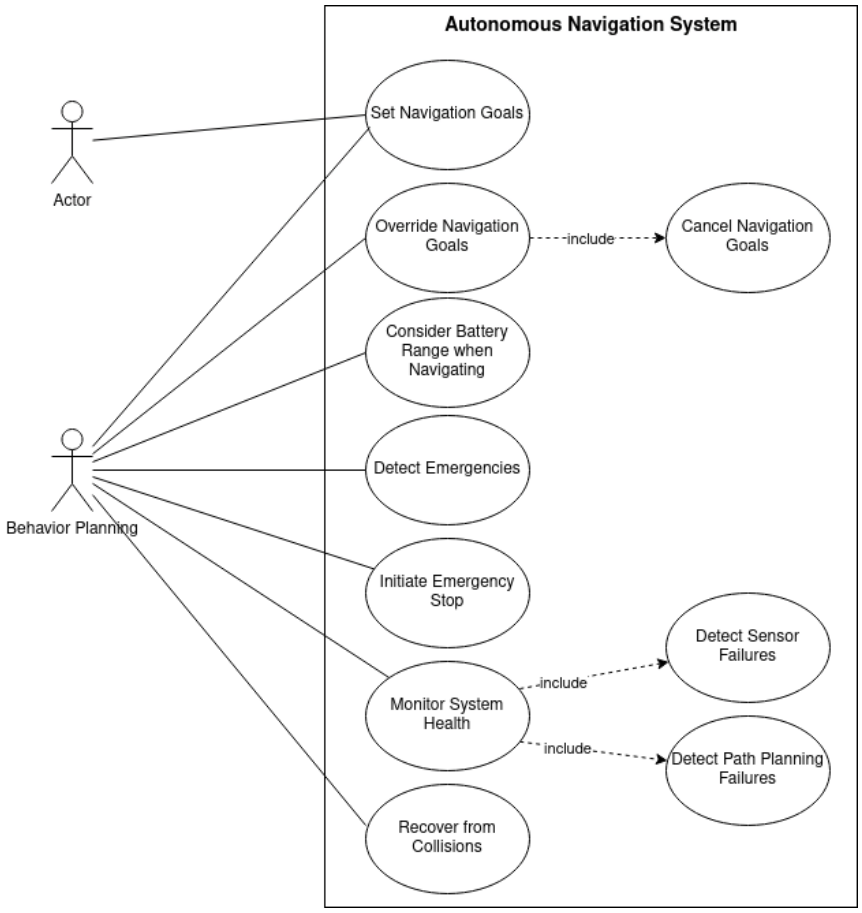



Figure 3.4: Use Case Diagram

to move. Also, an external system can more reliably monitor other systems when its execution is detached from the performance and execution of other systems.

A suitable name for the second system is the "autonomy layer", as its goal is to increase the robustness and autonomy of the whole system. The autonomy layer has to provide a comprehensive system supervisor that monitors all components' health (sensors, navigation, robot controller). The constant execution monitoring equips the system with the ability to deal with the event of node failures and component malfunctions.

Another required addition to the autonomy layer is a data storage of relevant system information and data. The stored data includes sensor data and generated maps, cost maps, positions, and speed commands. Using past data points allows behaviors to become more deliberative in their approach and opens up many possibilities for intelligent behaviors like movement predictions of obstacles.

A third component to the autonomy layer is a behavior planner largely independent of Nav2 execution and planning. This behavior planner must be capable of overriding the Nav2 behaviors if needed. The component processes information from the execution

checker, Nav2, and past and present sensor data to decide if and how to override the default behaviors. Based on this information, the behavior planner can make a deliberative, strategic decision to increase robustness and autonomy, thus decreasing reliance on human supervision.

Additionally, a component to switch intelligently between speed commands from Nav2 and the autonomy layer is needed. This component could be realized as a decision gate that receives speed commands from Nav2 and the new behavior planning component and can forward, block or modify commands sent to the controller. This modification aspect allows high-quality local planning capabilities but enables more deliberative behaviors to happen upon this planning. A simplified system block diagram is depicted in figure 3.5. The proposed additional components discussed in this chapter are colored in blue. Existing components, discussed in section 3.1, are colored in gray.

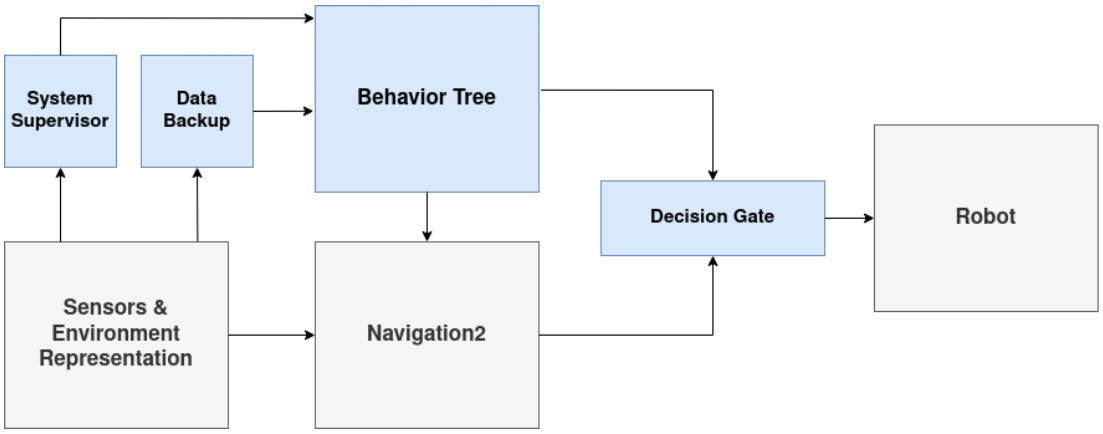



Figure 3.5: System Block Diagram

## 3.4 Software and Simulation

A comparison and assessment of the behavior planning approaches were made in section 2.4. The decision on which approach to use was made in favor of the behavior tree method. The main reason for this decision is the increased flexibility when creating and expanding the behavior planning compared to FSMs. Also, behavior trees allow complete determinism and introspection during execution which is why the POMPD approach is unsuitable as the primary behavior planning approach for the specified requirements.

### 3.4.1 Behaviortree.CPP

The Navigation2 stack uses a behavior tree to coordinate the planning layer. The behavior tree that is used is an expansion of the Behaviortree.CPP (BT.CPP) library. This library offers a way to create, execute, monitor, and edit behavior trees.

Additionally to the types of control nodes mentioned in section 2.4.2, the library adds the concept of reactivity into the catalog of control nodes. Reactive sequences and reactive fallbacks differ from normal ones in handling nodes that return the state "Running". Instead of ticking the node again, the whole sequence restarts, which is very useful for continuously checking a condition and executing an asynchronous action node that gets halted when a condition is not met anymore (see table 3.5).

Table 3.5: Control Nodes in BT.CPP

| **Name** | **Child returns Failure** | **Child Returns Running** |
|---|---|---|
| Sequence | Restart | Tick Again |
| Reactive Sequence | Restart | Restart |
| Sequence Star | Tick again | Tick again |
| Fallback | Tick next | Tick again |
| Reactive Fallback | Tick next | Restart |

Also, the library includes another class of Control Flow Nodes, called Decorator Nodes, which allow more control over the child node and its output. An essential distinction to other Control Flow Nodes is that Decorator Nodes can only have one child node compared to multiple children for sequence and fallback nodes. A comprehensive list of the available Decorators and descriptions is presented in table 3.6.

Table 3.6: Decorator Nodes in BT.CPP

| **Name** | **Succeeds** | **Fails** | **Running** |
|---|---|---|---|
| Inverter Node | If the child returns false | If child return success | If the child returns running |
| ForceSuccess Node | Always | Never | If child returns running |
| ForceFailure Node | Never | Always | If child returns running |
| Repeat Node | Ticks child as long as it returns success. Number of repeats can be defined | If the child returns failure | If the child returns running |
| Retry Node | If the child returns success | Ticks child as long as it returns failure. Number of ticks can be defined | If the child returns running |

To allow the tree nodes to communicate, the library provides the developer with two possibilities. Either node can use the blackboard, a dictionary (key/value) that all tree nodes can read and write. Alternatively, two nodes can be connected through ports which allows direct communication between two nodes via a key/value.

### 3.4.2 Groot

Groot is a program to create, edit, monitor, and debug behavior trees with a graphical user interface. The software allows the creation of behavior trees in XML files, which can be directly loaded into and used by the BT.CPP library. Groot can monitor the live execution of behavior trees and allows the introspection of how the tree reacts to different scenarios. Figure 3.6 shows a small segment of an active behavior tree.

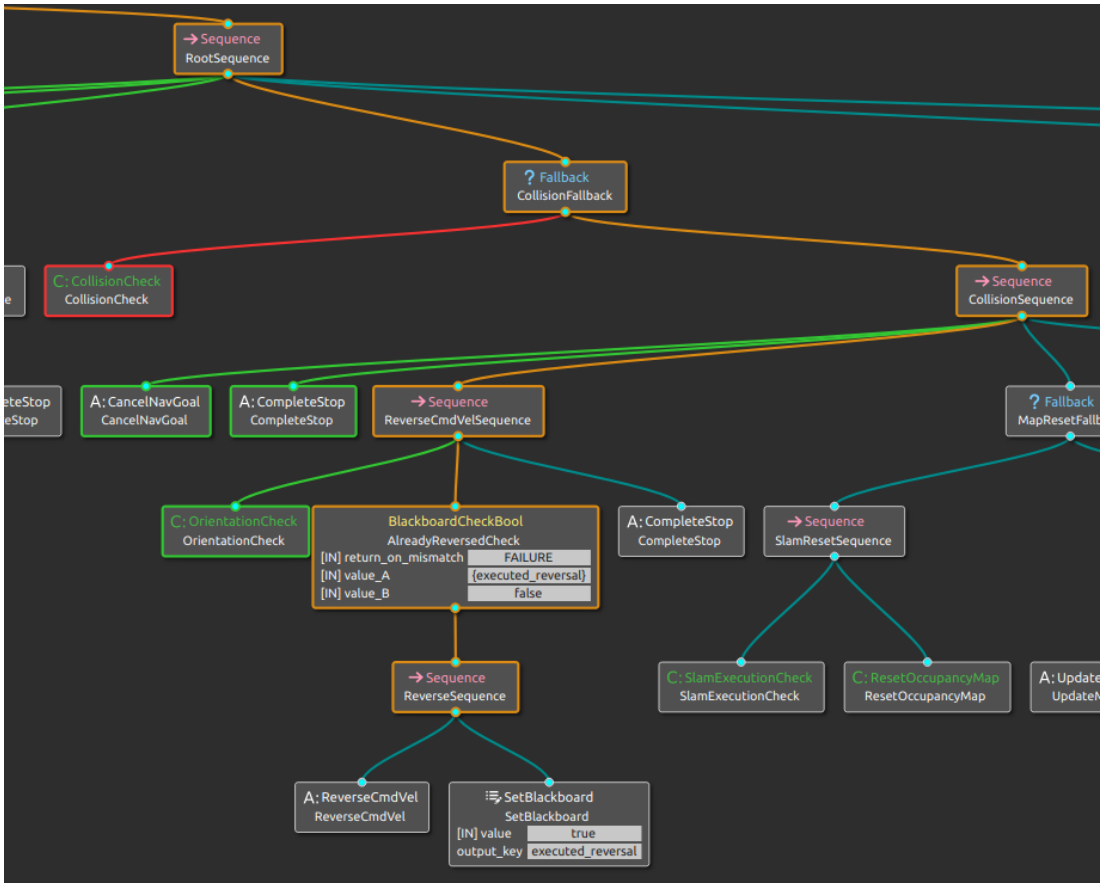



Figure 3.6: Live monitoring of behavior trees with Groot

In this graphical user interface, the condition nodes are labeled with a "C" before the node's name to distinguish them from action nodes which are tagged with an "A". The colors indicate the control flow and returned results of the respective nodes. A green box around a node shows that the tick signal got processed and returned "Success",

and a red box signals that the node returned "Failure". In the depicted example, the "CollisionCheck" node returned "Failure," and the fallback node ticked a sequence node called "CollisionSequence". The control flow has not returned to the sequence yet, which is why the sequence's border is colored orange. The depicted tree is executing an action node at the bottom of the figure named "ReverseCmdVel".

### 3.4.3 Gazebo Simulation Environment

The development and testing of behaviors are done with the Gazebo simulator and the Turtlebot3 model. Gazebo is well-integrated into ROS and ROS2 and offers many ROS interfaces to control the simulation. Gazebo accurately models the physics of the robot and can simulate and publish the wheel odometry directly on a ROS topic. Furthermore, Gazebo has an integrated ODE physics engine and can simulate the readings for the laser scanner and IMU data via plugins. The simulator allows easier repeatability for test cases as various obstacles can be spawned at any time, and sensor failures can be induced, resulting in quicker overall development.

Using a simulator facilitates slowing down or speeding up the environment time. The time control allows more intricate observation of fast reactive type behaviors in slow motion while also enabling the observation of the long-time robustness of the system during extended tests. The ROS community offers many different simulation environments to test the robot. The environments range from simple geometric structures to office spaces up to complete race tracks.

### 3.4.4 OS and Software Versions

The software versions used to implement and test the system are listed below in table 3.7. Many of the software versions are determined by the choice of the ROS distribution (distro). ROS2 Foxy is not the newest ROS2 distribution but is well supported and developed, so the decision was made to use this distribution. The decision why the turtlebot is used is laid out in section 3.1.2. Although Python and C++ can be used to develop applications with ROS2, the behavior tree library relies on C++, which is why C++ was used for developing the whole system.

Table 3.7: Used Software Versions

| **Name** | **Version / Release** | **Comments** |
|---|---|---|
| Operating System | Ubuntu 20.04 LTS | |
| ROS | ROS2 Foxy | Long-Term-Supported Distribution |
| Navigation2 | Foxy-devel | Newest Release for ROS2 Foxy |
| Simulation | Gazebo 11 | Determined by choice of ROS Distro |
| Robot | Turtlebot3 | |
| Behavior Tree | BT.CPP 3.7 | |
| Programming Language | C++ 14 | Determined by choice of ROS Distro |
| Build System | CMake and Colcon | Determined by choice of ROS Distro |
| Development Environment | Visual Studio Code | Offers IDE debugging options for ROS |

# Chapter 4

# Implementation

## 4.1 System Architecture

The system architecture, depicted in figure 4.1, integrates the autonomy layer discussed in section 3.3 into the current architecture.

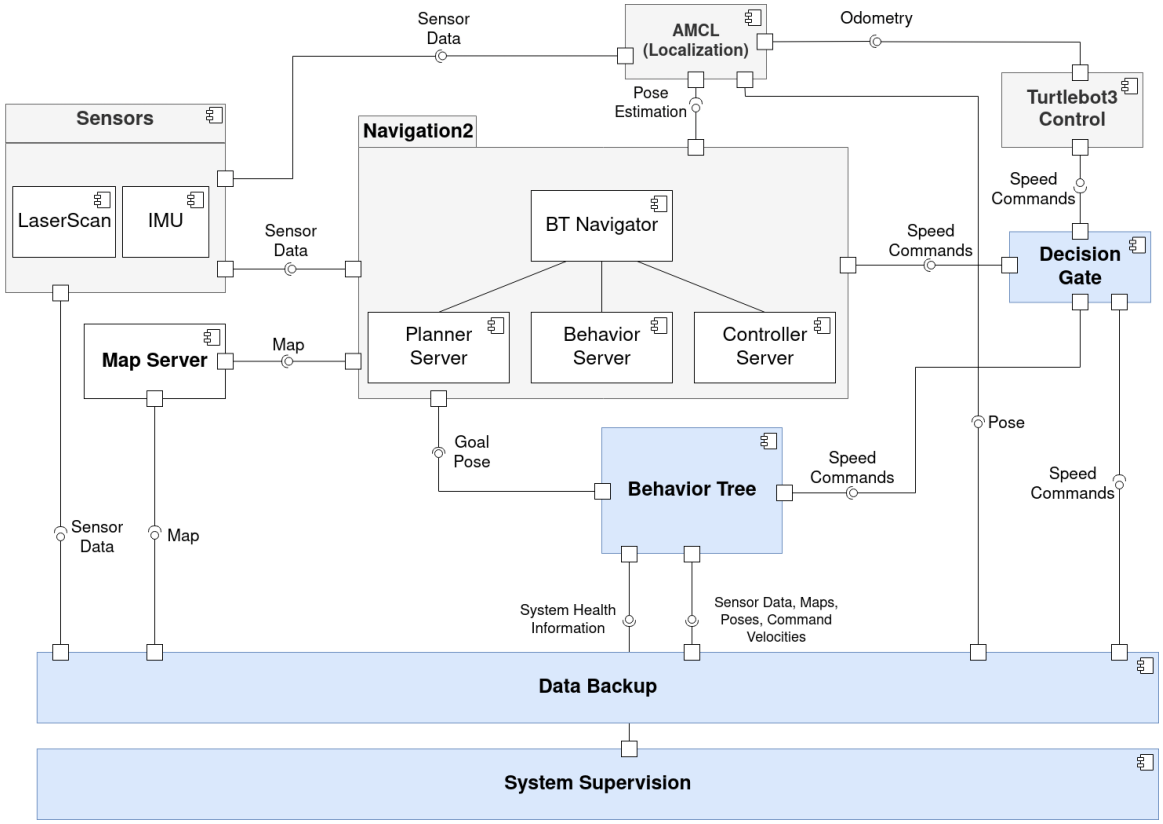



Figure 4.1: Component Diagram of System Architecture

Already existing components are colored in gray, while the components implemented in

this thesis (i.e., Data Backup, Decision Gate, Behavior Tree, and System Supervisor) are depicted in blue. The new components and their functions are described in the following sections of this chapter. The System Supervisor is explained in the BT section as a significant part of the component's functionality is realized inside the behavior tree.

## 4.2 Data Backup

The data backup component functions as a method to efficiently gather data from all system components and provide it to the behavior tree when the planning process requires past data points. This component subscribes to all sensor data and saves the messages in a queue data structure. The most recent data gets pushed into the array, and if the array exceeds a specified length, the oldest data this data gets deleted. There are two main reasons to limit the array size in this way. Firstly, the goal is to decrease the size of the message that gets sent to the BT to limit the network load. Secondly, the BT often does not need to look back further than a few seconds to make a decision. Subsequently, the computational and network load are decreased significantly. The saved data sources and corresponding lookback times are listed in table 4.1.

Table 4.1: Types of saved data

| **Name** | **Type** | **Lookback Time** |
|---|---|---|
| Lidar | Laserscan | 3 seconds |
| Poses | Pose with Covariance | 2 seconds |
| Map | Occupancy Grid | Only saved last one |
| Collision Pose | Pose with Covariance | Only last one |
| Command Velocities | Twist | 2 seconds |
| Global Costmap | Occupancy Grid | Only last one |

The BT can access the saved data by sending a service call to one of the provided services by this component. Service calls in ROS2 are executed with high priority and are done quickly. However, it adds steps to the algorithm instead of just saving the data directly in the behavior tree. The reason for outsourcing the data backup to another component is that the ROS node needs an executor which constantly spins the node. The spinning action checks the network to see if there is any work for the node. Work, in this context, means that if one of the subscribed topics receives a message, the node has to execute one of its callback functions associated with its subscription.

This spinning has to be done in regular intervals. Otherwise, the node might miss incoming messages from subscribed topics. This action inside the behavior tree thread would completely block the execution of the entire autonomy system. If one tries to spin a node only once when a node gets ticked in the BT, losing entire messages is a relevant concern because the BT might need longer than expected to return to a node to tick it. That way, the BT node responsible for saving all the relevant data cannot guarantee that it has received all the messages between spins as multiple messages might have been received between the two ticks. The synchronous nature of the ROS executor is why the data backup is not stored within the BT, but in an external ROS package to separate the threads.

## 4.3 Command Velocity Decision Gate

This component is responsible for modifying or blocking the Velocity Commands from Nav2. The component receives messages from Navigation2 on the "/cmd_vel_nav" topic and the "/cmd_vel_bt" topic from the behavior tree. This component publishes the received messages on the actual topic "/cmd_vel" which is subscribed by the robot controller. The BT can modify the Decision Gate parameters to either disregard incoming messages of Nav2 entirely or to modify them. The modification is helpful if the situation demands the robot to slow down.

If the Decision Gate receives messages from Nav2 and the BT, it will prioritize the BT. This situation should theoretically never occur as the BT will set the parameters for the Decision Gate accordingly and cancel the current Navigation Goal before publishing commands on its own. It is implemented as an additional safety measure in case the canceling of the goal is not possible if Navigation2 is not responsive to the cancelation command.

## 4.4 Behavior Tree Structure

A simplified behavior tree only depicting the top-level behavior control fallback nodes is shown in figure 4.2 on page 30. The tree receives the initial tick signal from the root in an infinite loop.

The root control node is a sequence node. The root node is a simple sequence because the whole system must function with increasing complexity in the tree's subsequent parts (located further on the right side of the tree). The complex behaviors require that all previous components and conditions work as they should. The root sequence will not allow

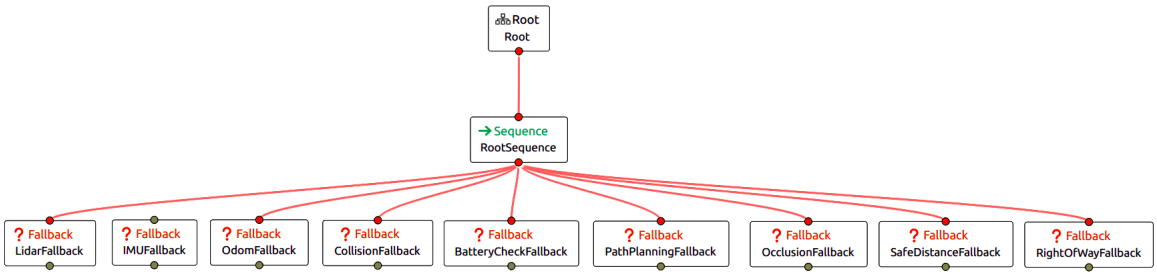



Figure 4.2: Top Level Behavior Tree Structure

the execution of higher-level behaviors if the system detects problems on more fundamental levels. The root sequence is the first step for increasing the system's robustness to combat competing reactive and deliberative behaviors that could endanger the robot's safety and other actors in its environment.

### 4.4.1 System Supervision

The system supervisor uses a "Watchdog" design pattern depicted in figure 4.3. A watchdog is used to monitor a system from the outside and take corrective measures when problems are detected.

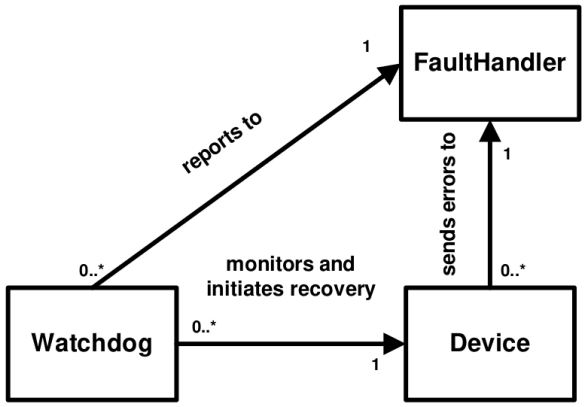



Figure 4.3: Examiner pattern for the system supervisor component [26]

The system supervisor component is partly outsourced into a component outside of the BT's thread for the same reasons as the sensor backup component discussed in the previous section. The synchronous executor would stop the execution of the whole behavior tree, which is why the component needs to be moved inside of a new thread. The system supervisor, also called the execution checker, receives messages from nodes not implemented as ROS2 lifecycle nodes. If a node stops sending messages or responding completely, the external execution checker can inform the BT via a provided service of a

problem with the node.

ROS2 lifecycle nodes provide information about their health via an FSM implementation inside the node. The current node state can be requested via a service call. However, the node's output needs to be checked, too, because it might be that the FSM inside the node does not pick up on an error and fails to change the internal lifecycle state.

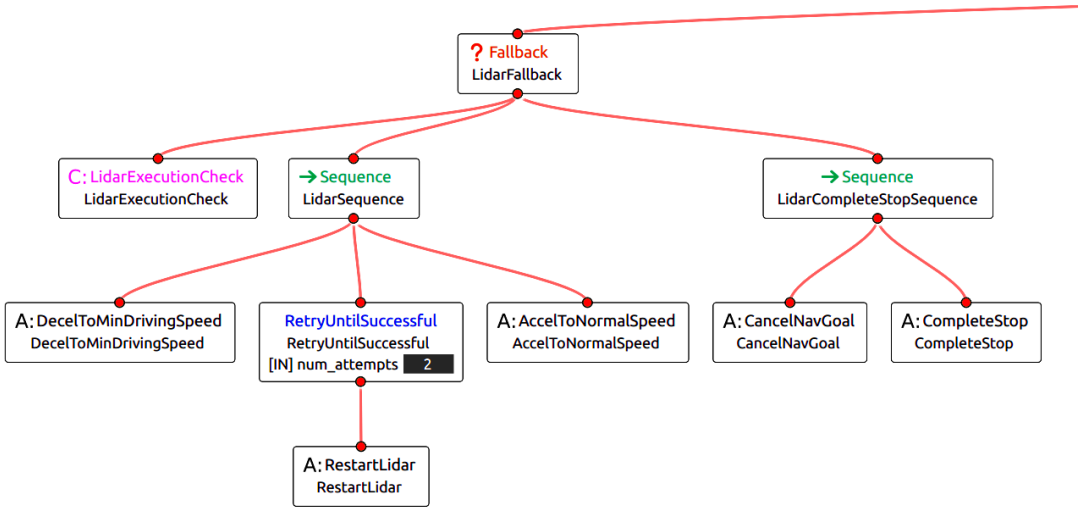



Figure 4.4: Lidar Fallback

The system supervision is constantly checking the system's health. The BT is using service calls to get the health information about the components checked inside Condition Nodes. The components get checked by the BT inside of a fallback node. If the condition for the execution is met, the condition node returns "Success", and the fallback would exit to move on to the next fallback and execution condition check as in the lidar fallback depicted in figure 4.4. If the execution checker detects a node failure, a sequence to react to the sensor failure is executed in which the robot slows down to a minimum and tries to restart the sensor. Should the restart fail twice, the robot will not be able to navigate safely anymore and will come to a complete stop. This behavior pattern is realized for the lidar, the IMU, and the wheel odometry.

The timeout period for the execution checker to declare a node failed after receiving no message is set to one second. After a sensor failure is declared, the goal of the sensor fallback depicted in figure 4.4 is to enable the robot to continue progressing towards the goal. However, if the system cannot restart the sensor in a short time after the failure, the robot has to come to a stop as a sensor failure is a severe function loss for the system.

### 4.4.2 BT Advanced Behaviors

After the BT has checked for sensor failures and can guarantee that the environment representation is accurate, the system can check for more complicated scenarios to improve autonomy. The implemented behaviors are outlined in this section.

#### Collision Behavior

One of the biggest problems mentioned in section 3.1 is the inability to react to collisions. The collision can happen due to inadequate sensory coverage for detecting obstacles or general sensor inadequacy, which cannot detect obstacles because of their shape or surface material. Collisions would be improbable with many sensors covering all angles and heights and computer vision capabilities to detect obstacles. However, even if the robot could detect all obstacles, it would still be vulnerable to outside perturbations (e.g., other robots driving into it or humans accidentally touching the robot).

In order to combat this weakness, the robot must be able to detect that a collision occurred, get out of the collision state, update the map and reset all costmaps to generate a new path to the original goal. The described behavior is depicted in figure 4.5.

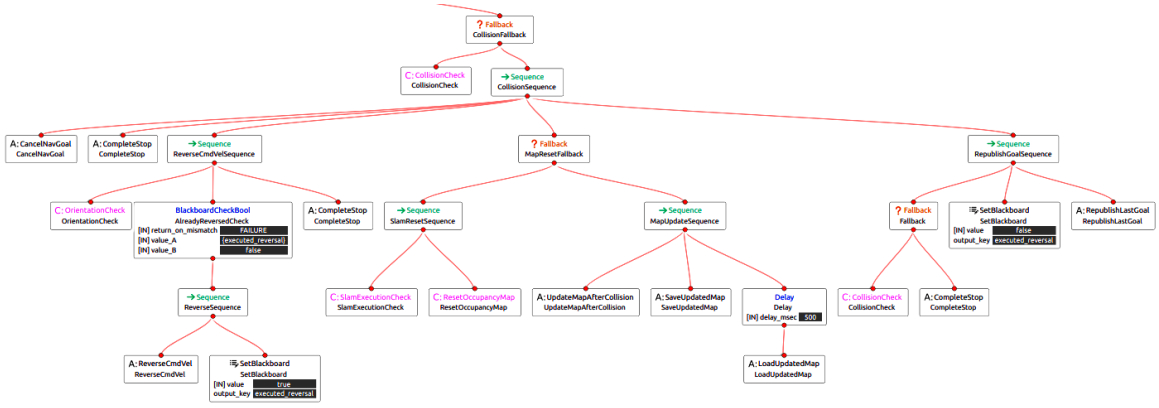



Figure 4.5: Collision Fallback Behavior

The collision checker uses a simulated sensor to detect collisions. On a real robot, the collision checker can use an IMU-based collision detection, but this has not been implemented in this behavior tree due to the time constraints of this thesis. The collision checker is integrated into the system supervisor, and the BT makes service calls to the execution checker to get the collision state of the robot periodically.

The child nodes of the collision sequence use the sensor data backup. To get out of the collision state, the BT requests the most recent command velocities from the data backup component and modifies them to reverse with minimum speed out of the collision.

The reversing action takes longer than the two seconds of saved commands as they get published with extended time intervals between them to adjust the driven distance to be the same as the original navigation commands. An additional check is implemented before reversing to ensure the robot only reverses once. Otherwise, the robot would drive back and forth as the data backup service would provide the BT with commands from the last reversing action.

Regarding the map reset, it has to be checked if a new map is being created with a SLAM method or if the map server provided a previously saved map. In the case of the running SLAM, the recent updates to the map must be discarded and a previous map version before the collision has to be re-utilized. If the map server component from Nav2 provides a static map, the map needs to be updated with a new obstacle at the point of collision and republished by the map server.

The activity of the "MapUpdateAfterCollision" action node is depicted in figure 4.6 on page 34. The collision point is estimated by the robot's pose, which refers to the robot base link and the robot footprint. It is assumed that the collision point was right in front of the robot because the local planner favors forward drive kinematics and probably is driving forwards when a collision occurs. The simulated bumper sensor can provide more nuanced information about the point of contact. However, this functionality can only be achieved with high developmental effort on a real robot with IMU-based collision detection. In order to limit the effort of transferring and running the implemented software on a real robot, the obstacle position is simplified to always be directly in front of the robot. A 25 by 25 $cm$ square with 100 percent occupation at the collision point is added to the current map and then saved to be reloaded by the map server. The original goal is then republished to replan the global path on the updated map..

This way, obstacles lower than the lidar scan height can be detected. With this behavior, the robot should be able to eventually navigate around transparent obstacles that do not reflect the laser. Glass doors are known to cause issues for lidar-based robots because of their reflective properties (see section 3.1.3).

### Battery Behavior

The battery behavior aims to monitor the robot's battery and has to decide if the robot should navigate to a new goal location or not. The decision is based on the current battery charge and the estimated consumption of energy to reach the new goal. The robot should not begin the navigation process if it is probable that the remaining charge will not suffice to arrive at the goal. Figure 4.7 on page 35 depicts the battery fallback.

The behavior has to consider the idle consumption and the energy to drive the motors.

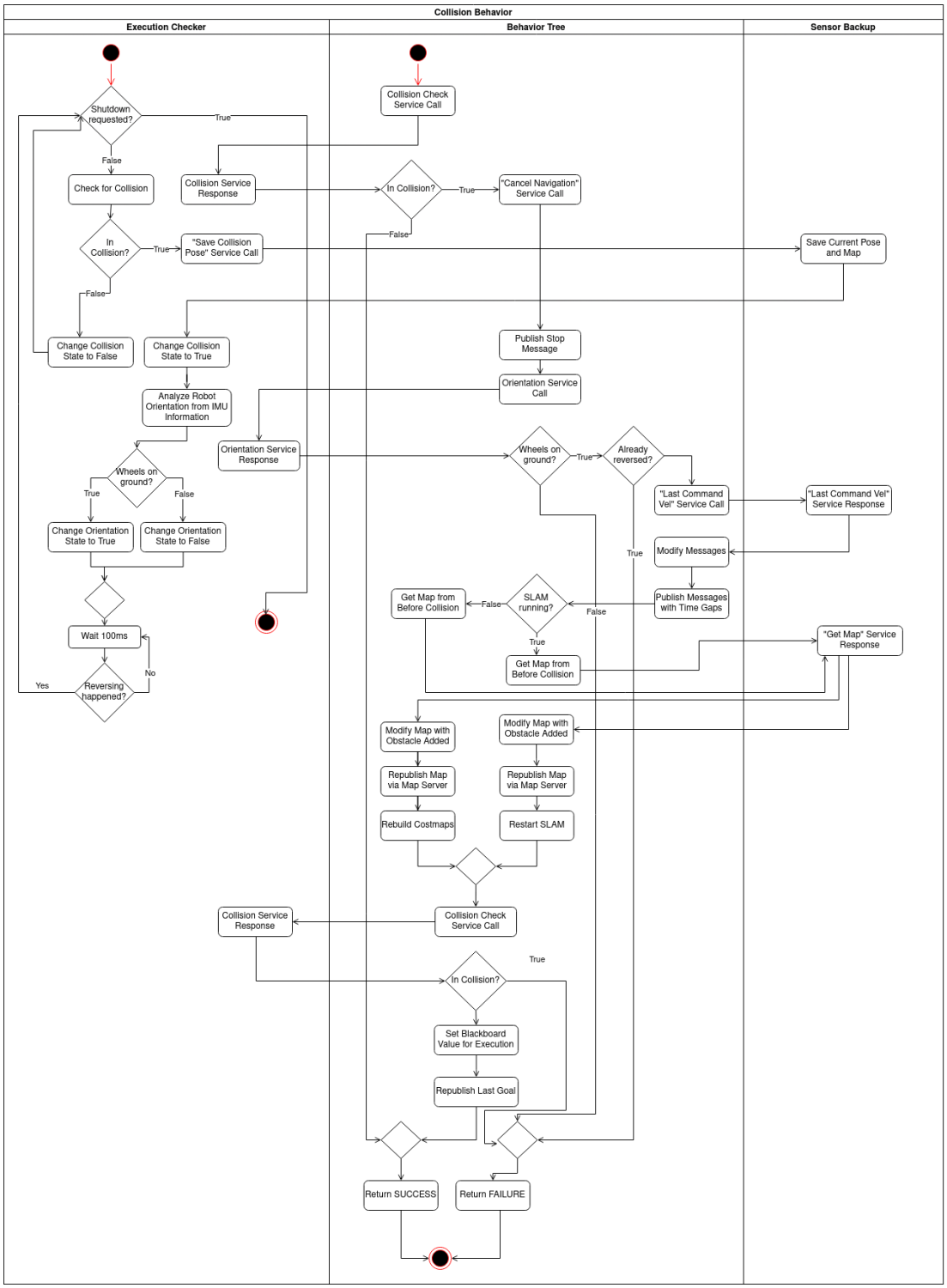



Figure 4.6: Activity Diagram for the Collision Behavior

With this information, a linear function for energy expenditure was created to predict battery usage depending on the path length. An additional safety factor was added to the

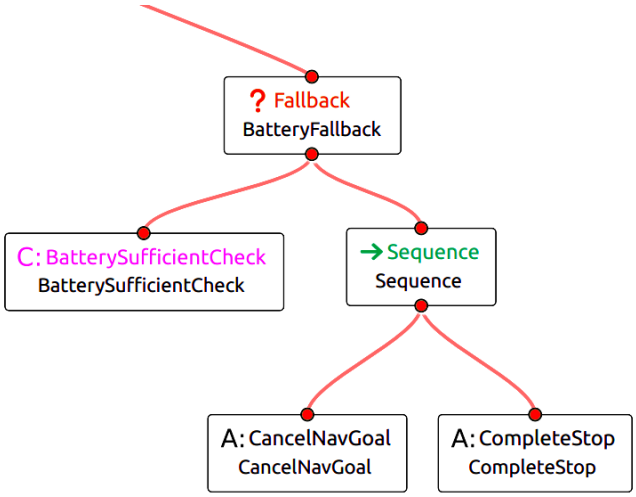



Figure 4.7: Battery Fallback Behavior

energy estimation function to consider the scenario in which the robot must reroute and drive a longer route or stop for a moment. The safety factor was included to increase the behavior's robustness and cover more scenarios.

A battery package was created for the simulation, which updates the battery charge every second. The battery package subscribes to the command velocity topic and decreases the battery charge for every message received. The battery package was created because the behavior needs to be tested, but Gazebo does not offer this functionality. The consumption rates are not close to reality but are chosen to allow for rapid testing of the behavior. The average values for idle and driving consumption on a real robot could be experimentally determined.

The battery package provides a service to get the battery charge and the values for the assumed consumption rates while idle and driving (compare 4.2. The BT node "IsBatterySufficientCheck" calls the service to compare the current battery to the calculated consumption. The battery behavior fallback will cancel the navigation goal if the robot cannot reach the given goal with the remaining charge.

### Path Planning Behavior

With this behavior, a way to make the global planner more flexible was implemented. The execution checker component monitors the health of the Nav2 global planner. Additionally, the behavior tree analyzes the global planner's output. If the latter condition fails, the given navigation goal is not reachable by the planning algorithm. By shifting the goal to a nearby alternative goal, the robot tries to navigate to a close location, although the original goal cannot be reached.

If the location is still unreachable, the goal gets moved further away from the original. The routine repeats up to ten times, leading to a maximum distance to the original goal of up to one meter. The goal gets moved on a straight vector towards the robot. This behavior did not implement other strategies for finding alternative goals due to time constraints of the thesis. Figure 4.8 depicts the behavior tree fallback for the behavior.

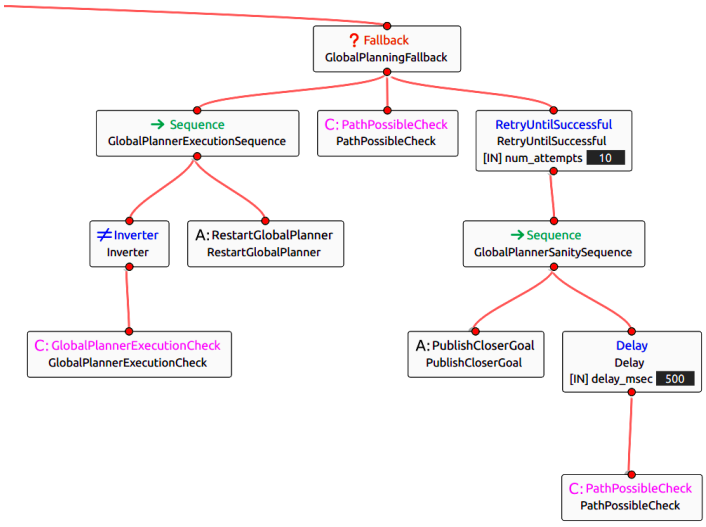



Figure 4.8: Path Planning Fallback Behavior

## 4.5 System Support Tools

### 4.5.1 Gazebo Sensor Drivers

For testing purposes, the simulated sensor data is not published directly on the actual topic by Gazebo. An intermediary node is used, which subscribes to the Gazebo topic and republishes the information on the original topic. The failure of a sensor can be simulated this way by stopping the execution of the intermediary node.

### 4.5.2 Custom ROS Interfaces

Because of the necessity to have ROS nodes spinning outside of the BT thread, as discussed in section 4.4.1, additional interfaces are created to receive information through service calls. The created service types are listed in table 4.2. All service definitions are created in a dedicated package named ”bt_msgs”.

Table 4.2: Implemented Custom Services

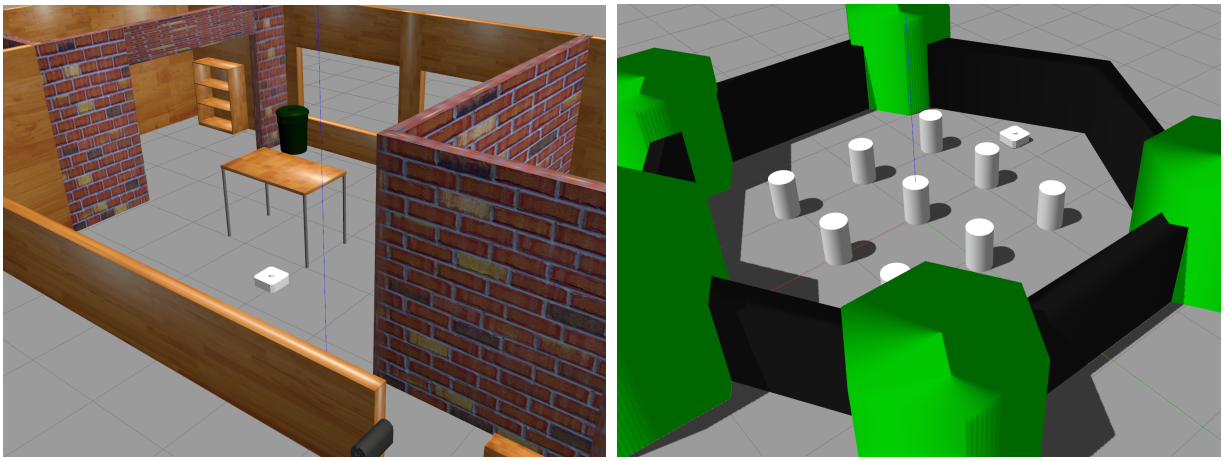
| **Name** | **Request** | **Response** |
|---|---|---|
| GetCharge | Empty | float charge, float idle_decrease_per_sec, float drive_decrease_per_sec |
| GetDistance | Empty | float distance_in_meter |
| GetLastGoal | Empty | geometry_msgs/Pose last_goal_pose |
| GetLastMap | Empty | nav_msgs/OccupancyGrid map |
| GetTwistArray | Empty | geometry_msgs/Twist[] cmd_vel_array |
| PubCmdVel | geometry_msgs/Twist cmd_vel, float time_in_seconds | bool success |
| SendUpdatedMap | nav_msgs/OccupancyGrid updated_map | Empty |

# Chapter 5

# Evaluation

The robot is put into specific scenarios to trigger behavior responses from the behavior tree component. The scenario testing is done to evaluate the efficacy of the implemented behaviors in relation to the functional requirements listed in section 3.2.

The scenarios are executed in a simulated apartment environment as seen in figure 5.1a and a simulated world with small round obstacles in an enclosed space as depicted in figure 5.1b. The environments were mapped beforehand with the ROS2 "Slam Toolbox" package and provided by the Nav2 map server.



(a) Apartment Environment in Gazebo (b) Enclosed Environment in Gazebo

Figure 5.1: Gazebo World Environment

The robot location and navigation goals are defined in another ROS node, which programmatically spawns the robot into the environment and sets the goal this way. This way, the same scenario can be run with and without behavior planning. To test the behavior of the sensor failure fallbacks, the respective sensor driver, mentioned in section 4.5.1, was shut down to emulate the sensor's failure.

## 5.1 Scenarios

The scenarios are derived from the functional requirements and can be used to test multiple requirements as listed in the tables 5.1 and 5.2. The acceptance criteria often contain multiple binary conditions that can only be met or failed. All acceptance criteria for a given scenario must be met for the test to be counted as a success.

Table 5.1: Sensor Scenarios

| **Sensor Tested** | **Name** | **Requirements** | **Description** | **Success Criteria** |
|---|---|---|---|---|
| Lidar | Lidar_1 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Robot is standing still, Lidar node crashes | Reset the system |
| | Lidar_2 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Navigating with 0.25 m/s straight towards goal (1m away) | Reset system, reach goal |
| | Lidar_3 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Navigating with 0.25 m/s and 0.5 rad/s towards goal (1m away) | Reset system, reach goal |
| IMU | IMU_1 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Robot is standing still, IMU node crashes | Reset system |
| | IMU_2 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Navigating with 0.25 m/s straight towards goal (1m away) | Reset system, reach goal |
| | IMU_3 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Navigating with 0.25 m/s and 0.5 rad/s towards goal (1m away) | Reset system, reach goal |
| Odometry | Odom_1 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Robot is standing still, Odom node crashes | Reset the system |
| | Odom_2 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Navigating with 0.25 m/s straight towards goal (1m away) | Reset system, reach goal |
| | Odom_3 | fn_req1, fn_req2, fn_req3, fn_req4, fn_req5 | Navigating with 0.25 m/s and 0.5 rad/s towards goal (1m away) | Reset system, reach goal |

The scenarios were conducted in different ways described in the following paragraphs.

For the lidar, IMU, and odometry scenarios, the sensor driver was shut down when reaching the desired speed listed in the scenario. The location and goal are given as described in the previous chapter. Each sensor was tested multiple times in three different

Table 5.2: Behavior Scenarios

| **Name** | **Requirements** | **Description** | **Success Criteria** |
|---|---|---|---|
| NoPath Found_1 | fn_req7 | Path to goal can not be calculated, robot is standing still | Reset system, calculate path to goal, reach goal |
| NoPath Found_2 | fn_req7, fn_req8 | Goal is unreachable, robot is standing still | Alternative goals, close to the original are tested to be reachable |
| Collision_1 | fn_req2, fn_req4, fn_req6 | Robot is standing still and a collision with the robot is caused | Robot can get out of collision state, navigation to goals still working |
| Collision_2 | fn_req2, fn_req4, fn_req6 | The robot is driving and collides with an undetected obstacle (0.25m/s) | Robot can get out of collision state, navigation to goals still working, undetected obstacle gets added to map |
| Battery_1 | fn_req9 | The robot battery runs low | The robot will not drive to a goal that is outside of its reachable range |

driving situations.

NoPathFound_1 is a scenario in which the lifecycle state of the global planner gets transitioned into "inactive" and cannot execute the planning action anymore when triggered. The BT has to recover from the inability to plan in this scenario. NoPathFound_2 simulates that the planner is active but fails to find a collision-free path to the desired goal. This scenario tests the ability to find alternative goals and navigate to a nearby goal.

In the Collision_1 scenario, an obstacle gets moved so close to the robot that a collision is registered. The forced collision tests the ability to maneuver out of a collision and resume navigation afterward. A new navigation goal is published after the behavior tree exits the Collision Fallback Routine. Collision_2 tests the same behavior but during active navigation. A flat obstacle is spawned in the path of the robot. The obstacle is too low to be detected by the laserscanner, and a collision occurs. The robot must be able to recover from the crash and keep on navigating towards the goal with an updated global path.

The Battery_1 scenario tests if the robot tries to navigate toward a distant goal with a low battery charge. The simulated battery is emptied to a low level, and a new navigation goal is set. The test fails if the battery charge runs below zero percent during the navigation.

## 5.2 Results

The results in table 5.3 show an increase in the successful handling of the test scenarios for most test cases. The system supervision component is very reliable and enables the

system to recover from an unexpected sensor failure. The more advanced behaviors can improve the autonomous handling of the scenarios. The Battery Scenario was successful every time it was induced. However, the path planning behavior for finding alternative goals was unsuccessful about 50 percent of the time.

The collision behavior during driving worked well, and the map updates are an essential feature for the success of the test scenarios. Nevertheless, there is a lack of intelligence and autonomy when the robot stands still, and a collision is forced. The implemented behavior relies on the same mechanism as during the driving scenario. The missing differentiation led to a test case where the robot reversed into a wall because it was turned 90 degrees by the collision. Therefore, the test failed because a human operator would be needed to correct the robot's position. This lack of robustness was not apparent in the driving collision scenario because the robot's force was insufficient to cause a significant shift in orientation when colliding with obstacles.

The results show that the functional requirements (as defined in 3.2) are met in almost all cases. Fn_req1 to fn_req5 are all completely fulfilled. Fn_req6 is only partly fulfilled as the test showed potential shortcomings of the implemented collision behavior. Fn_req7 satisfies the acceptance criteria, but fn_req8 is only partly met by the implemented solution to find alternative goals. Finally, the battery behavior meets all acceptance criteria, and thus fn_req9 is fulfilled.

The architectural design choices meet all the non-functional requirements. Implementing the behavior planning and system supervision system eliminates a single point of failure for the system. Even when the Navigation2 system collapses, the robot can move to a degree and, more importantly, stop completely (compare table 3.3, non_fn_req). The behavior tree and algorithms implemented in the behavior tree are all deterministic (non_fn_req3). The robots' behavior goes beyond pure reactivity when navigating through environments, as the advanced behaviors use a dedicated planning phase before the actions are carried out (non_fn_req4).

Finally, the system's performance when checking the conditions of the BT is below the desired threshold of 10ms, as the whole system runs in multiple threads, which allows the behavior tree to complete one complete execution cycle in about 5ms with the current system. (non_fn_req2).

Table 5.3: Results

| **Name** | **Number of Runs** | **Percentage Successful** | |
|---|---|---|---|
| | | **Without Behavior Planning** | **With Behavior Planning** |
| Lidar_1 | 5 | 0 | 100 |
| Lidar_2 | 5 | 0 | 100 |
| Lidar_3 | 5 | 0 | 100 |
| IMU_1 | 5 | 0 | 100 |
| IMU_2 | 5 | 0 | 100 |
| IMU_3 | 5 | 0 | 100 |
| Odom_1 | 5 | 0 | 100 |
| Odom_2 | 5 | 0 | 100 |
| Odom_3 | 5 | 0 | 100 |
| NoPath Found_1 | 20 | 0 | 100 |
| NoPath Found_2 | 20 | 0 | 55 |
| Collision_1 | 20 | 0 | 95 |
| Collision_2 | 20 | 0 | 100 |
| Battery_1 | 10 | 0 | 100 |

# Chapter 6

# Conclusion

This thesis demonstrated how to incorporate advanced behavior planning in ROS2 mobile robots. The goal was to achieve higher levels of autonomy and robustness by reducing the number of scenarios in which a human operator is needed. Implementing the system supervisor component improved the system's robustness and provided a safe basis for executing more intelligent behaviors. The implemented behaviors to react to sensor failures and robot collisions were valuable improvements to the system and improved current ROS2 mobile robots significantly. The layout of the behavior tree was structured to allow more complex behaviors to be safely executed because possible scenarios that interfere with a correct environment representation were checked and dealt with before complex behaviors get executed based on that representation. The implemented layout choice for the tree was not mentioned in previous literature. However, it has proven to be a sensible approach to model robot behavior safely and robustly.

Furthermore, the system architecture is a good base for further development without facing problems or limitations in the later stages of developing behaviors. The architecture showed a novel way that works with the ROS2 executor properties and allowed fast execution of both the behavior planner and the system components.

Nevertheless, the behavior tree design could have been modified to use blackboard values more effectively to increase the information flow between action nodes in the tree. Also, the tree did not utilize the reactive control flow nodes, and no action node in the tree was designed to allow multiple threads at the current state. Incorporating so-called stateful nodes into the tree's structure to allow co-routines would have increased the possibility of creating better and more deliberative behaviors.

# Chapter 7

# Outlook

Firstly, the results must be reproduced on an actual mobile robot. The layout of the behavior tree will stay the same, but further effort is needed to adapt the action nodes of the tree for a real system.

The implemented behaviors were a first step to increasing autonomy, but the behavior planner needs more behaviors and fallbacks. Some crucial behaviors not implemented in this thesis incorporate the Intel RSS rules for autonomous driving, like keeping appropriate distances, right-of-way rules, and adaptable speed based on occlusions. Further, the implemented collision detection needs to be refined to allow collision point detection to improve the behavior's robustness. Also, the strategy for finding nearby alternative goals in the path planning behavior needs to be modified or changed to sample more points in all directions around the given goal.

Another area of future work is the creation of dedicated behaviors for multi-robot systems. For example, robots could share sensor data to overcome complete sensor failures or intelligent path planning to avoid collisions when robots can access the planned paths of other robots. Also, more work is needed to define a robot's safe state or position after triggering an emergency stop. Reaching these minimum risk states after emergencies is then the duty of the behavior planner.

Intelligent, robust, and independent decision-making almost always involves machine learning (ML) which makes decisions based on training data and not written lines of code. This property makes ML nondeterministic and, therefore, unsuitable for many high-risk and safety-relevant applications. Therefore, an important area of future work is how ML algorithms can be incorporated into a deterministic system like a behavior tree. A behavior tree could execute and monitor the ML behaviors to safeguard and override them if necessary with explicitly programmed but still highly automated behaviors.

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