Reconfigurable Behavior Trees: Towards an Executive Framework Meeting High-level Decision Making and Control Layer Features

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Abstract—Behavior Trees constitute a widespread AI tool which has been successfully spun out in robotics. Their advantages include simplicity, modularity, and reusability of code. However, Behavior Trees remain a high-level decision making engine; control features cannot be easily integrated. This paper proposes the Reconfigurable Behavior Trees (RBTs), an extension of the traditional BTs that considers physical constraints from the robotic environment in the decision making process. We endow RBTs with continuous sensory information that permits the online monitoring of the task execution. The resulting stimulus-driven architecture is capable of dynamically handling changes in the executive context while keeping the execution time low. The proposed framework is evaluated on a set of robotic experiments. The results show that RBTs are a promising approach for robotic task representation, monitoring, and execution.

I. INTRODUCTION

Modern robotic agents demand increased flexibility in the way the assigned task is represented and executed. Indeed, autonomous robotic systems need to be capable of dealing with sensing and planning operations at low cost, as well as monitoring actions in a goal-oriented fashion [1]. Behavior Trees (BTs) constitute a powerful tool for task switching and AI decision making which is receiving an increased amount of attention in the robotic community [2]–[4]. The reason for this growing attention mostly depends on the fact that BTs are self-explanatory, modular, code reusable, and simple to design. A Behavior Tree is built combining a limited number (six) of node types. This greatly simplifies the design of new BTs, makes them human-readable, and eases the formal verification of the generated task plan without penalizing their expressive power [3]. Behavior Trees are also modular in the sense that each subtree may be seen as a subblock which may be added or replaced by any other subblock. This makes the code reusable for different applications and further simplifies the design of new BTs.

However, Behavior-Tree engines are not designed to operate within the sense-plan-act paradigm, nor do they provide an optimized trade-off between reactiveness and execution cost for low-level control. Besides this, Behavior Trees may easily grow when the number of actions and conditions needed for closing the execution loop increases. Moreover, the continuous monitoring of the task execution as well as the online resolution of possible ambiguities in the task plan are typically not supported by BTs. In order to overcome these limitations, a robotic executive framework has to: \(i\) ensure low complexity in terms of cost and implementation when dealing with task executions, \(ii\) make a connection between low-level stimuli and high-level decision making, and \(iii\) enable a planning approach while keeping the control on the end goal.

This paper proposes an executive framework that meets the robotic task requirements by combining the BTs planning capabilities with attentional mechanisms for control features [5], [6]. The proposed Reconfigurable Behavior Trees (RBTs) exploit the high modularity of traditional Behavior Trees to define a tree structure that can be reconfigured at runtime, i.e. dynamically during the task execution, by adding and/or removing parts of the tree. The reconfiguration is ruled by environmental stimuli corresponding to changes in the sensed information and by the successful execution of goal-directed actions. This paper presents a formal definition of the RBT framework and evaluates the performance of the proposed framework in a set of robotic experiments.

The outline of this paper is as follows. Section II presents related work. In Sec. III we describe the proposed approach. Section IV presents simulation experiments and evaluates the results. Section V states the conclusions and proposes further extensions.

II. RELATED WORK

Finite State Machines (FSMs) have been widely used in different areas of computer science and engineering. A FSM provides a basic mathematical computational model consisting of a definite set of states, transitions, and events. FSM are flexible and easy to design, but as soon as the system grows in complexity, a reactivity/modularity trade-off problem arises and the FSM becomes impractical.

Decision Trees (DTs) [7], the subsumption architecture [8], and the sequential behavior compositions [9] are widely-used approaches to decision making and task execution in robotics. A DT is an analytical decision support tool consisting of control structures and predicates located in the leaves and nodes, respectively, which map the possible outcomes of a series of choices. The motivation for its usage relies on the “white-box” method, i.e. decisions can be intuitively explained, they are simple to visualize, and may be easily implemented. However, DTs lack robustness in case of noisy perceptual data and their size rapidly increases in complex scenarios. The subsumption architecture relies on
having a number of controllers in parallel which are ordered with different priorities so that each one is allowed to output both actuator commands and a binary value, signaling if the control of the robot is active or inactive. In the sequential behavior compositions the state space is split into cells, and each cell is associated with a unique, predefined controller.

Colledanchise and Ögren [3] have shown that Behavior Trees (BTs) represent an elegant generalization of FSMs, DTs, subsumption architecture, and sequential behavior compositions. Several fixed-logic control models have emerged that extend BTs functionalities and attempt to overcome the limitations of BTs in highly dynamic environment. For instance, Conditional Behavior Trees [10] extend traditional BTs to monitor the execution of the action considering logic pre- and postconditions. The work in [11] proposes to cast an automated plan created by a Hierarchical Task Network (HTN) planner [12], [13] into executable BTs. In this way, Behavior Trees provide reactiveness and modularity, whereas the planner is responsible for the deliberative behavior of the robot. Along the same lines, the work in [4] combines a Fast Downward planner [14] with BTs. The resulting extended Behavior Tree is responsible for describing how to execute a procedure and, at the same time, its effects on the world state. In this way, the robot can employ abstract skills for planning sequences and adjust and optimize them for task execution. Other approaches extend BTs by integrating models where domain knowledge could be learned automatically, for instance using reinforcement learning [15], genetic programming [16], or imitation learning [17]. Learning techniques would overcome the limitations of classical planners that require significant engineering effort [18]. Finally, the work in [19] attempts to map the practical solutions developed for action sequencing in real-time strategy games to robotic applications.

Facets like human-readability, expressivity, modularity, and reusability make BT-based techniques popular and unquestionably attractive. However, critical aspects that these approaches do not cover are the connection to the physical executive state and the possibilities of ambiguities in the decision making. Their rigidity is not optimal for systems with strong perceptual constraints, like robots intended to interact with the environment and able to flexibly behave and react to unexpected events. To tackle this issue, some work exploits attentional mechanisms for visual task learning [20], for cognitive control of humanoid robots [5], and for flexible orchestration of cooperative tasks [6]. Inspired by the way humans monitor and orchestrate task execution [21], [22], the attentional framework in [6] load tasks from a long-term memory and instantiates them in a working memory using a mechanism analogous to that used in HTN planning [12]. Additionally, continuous sensory data are exploited to solve any ambiguities in the task plan and to quickly react to environmental changes. This attentional system has been effectively integrated in an imitation learning framework to learn, plan, and monitor complex robotic tasks [23]–[25].

In this work, we take the best of these two worlds and propose Reconfigurable Behavior Trees (RBTs), an executive framework that combines the human-readability, modularity, and reusability of Behavior Trees with the additional flexibility offered by attention-based cognitive architectures.

### III. RECONFIGURABLE BEHAVIOR TREES

#### A. Behavior Trees

A Behavior Tree is a graphical model language to control the behavior of an autonomous agent and execute a task. A BT consists of a tree structure containing a combination of the six types of nodes shown in Tab. 1. These types are divided into two categories: control flow and execution nodes. The four types of control flow nodes are Sequence, Fallback/Selector, Decorators, and Parallel nodes. The two types of execution nodes are Condition and Action nodes. Each type of node returns a running state during the execution and success or failure after the execution. The execution of a Behavior Tree is possible by periodically traversing the tree from the root node to all child nodes from left to right. The traversing mechanism is periodically activated by sending a signal called “tick”. Each child node responds to this signal according to its own type and to the return state of the other nodes. Table I describes the behavior of each type of node for the Success and Failure cases. The running state will behave in a similar fashion.

A minimal example of a Behavior Tree applied to a pick-use-place object task is shown in Fig. 1. The root being a Sequence node, the BT is executed sequentially from left to right. If the condition object picked has not been fulfilled, i.e. the node returns False, the action node pick object enters the Running state. The action node returns success upon successful completion of the pick action. As a consequence, the first (far left) Fallback node also returns success and the traversal mechanism enters the second (middle) Fallback node. This procedure is repeated

| Type                | Symbol     | Success           | Failure          |
|---------------------|------------|-------------------|------------------|
| Fallback/Selector   | ?          | One child succeeds| All children fail|
| Sequence            | →          | All children succeed | One child fails |
| Parallel            | ≥M         | >M children succeed | >N − M children fail |
| Decorator           | ◦          | Custom            | Custom           |
| Action              | □          | Upon completion   | Impossible to complete |
| Condition           | ⊙          | True              | False            |

![Fig. 1. A Behavior Tree representing a pick-use-place task.](image-url)
until all the Fallback nodes return success, indicating that the task has been successfully completed.

B. RBTs components

The generic Reconfigurable Behavior Tree (RBT), depicted in Fig. 2, is a Behavior Tree enriched with extra functionalities that permits the continuous monitoring of environmental stimuli and the dynamic reconfiguration of the tree to execute. Interestingly, those functionalities are implemented using the same six types of nodes considered in the standard BTs (see Tab.I), leaving unaffected the design simplicity typical of BTs. Traversing the RBT from the root (Fallback) node, we first check if the end goal of the task is fulfilled. If not, we check if the blackboard is initialized and eventually run initialize blackboard. The blackboard is a mechanism used in BTs to store and update runtime variables and to make them accessible by each node in the tree. In the RBT framework, the blackboard contains the logical pre- and postconditions used to regulate the task execution and to determine when the task goal is fulfilled, the sensed information used to set the priorities of each subtree, and the current value of the subtrees priorities. The blackboard is dynamically updated and greatly simplifies the communication between nodes by handling the concurrent access in a transparent and thread safe manner. We would like to point out that that this part of the RBT, surrounded by a gray polygon in Fig. 2, allows execution to be terminated after a global goal is reached. A similar branch has to be introduced in the standard BT to successfully terminate the task and therefore is does not introduce extra nodes in the RBT. Once the blackboard is initialized the right branch of the RBT is traversed and two parallel processes start. On one side, sensory data are processed to determine the priority of the $S$ available subtrees. On the other side, the most emphasized subtree is instantiated and executed asynchronously with respect to the perceptual input. The instantiation mechanism is dynamic and allows for flexible task orchestration.

Compared to a BT, the RBT has the following extra components:

1) A Long-Term Memory (LTM) and a Short-Term or Working Memory (WM) that are typical in attention-based control frameworks [6].
2) A priority handler, namely the Emphasizer, that computes the highest-priority task considering the sensed information and logical pre- and postconditions.
3) An Instantiator that accesses the LTM and casts the subtask into the corresponding subtree loaded in the WM. The Instantiator enables the RBTs reconfiguration capabilities by dynamically loading and instantiating the subtree with higher priority.

The distinctive components of RBTs are detailed in the rest of this section.

C. LTM and WM

The LTM can be considered a database that contains all subtasks that the robot is able to execute. A typical subtask is the pick-use-place object task described in Sec. III-A. In order to store and retrieve subtasks from the LTM, we propose a common representation of the 4 control flow nodes in Tab. I. The generic control flow node $B$ is represented as a quadruple

$$B = (l, t, c, p) \quad (1)$$

where $l$ is the unique name (label) of the node, $t$ is one of the types in Tab. I, $c$ is a list of children, and $p$ is a list of parameters like the priority value or pre- and postconditions.

In principle, it is possible to represent also the 2 execution nodes in Tab. I as the quadruple defined in (1). However,
we found a more convenient way of exploiting the fact that execution nodes correspond to leaves in the BT. In more detail, action nodes are specified only in the children list of the father node, while the condition nodes are used to represent the pre- and postconditions that are listed in the parameter list \( p \). The successful execution of an action also changes the state of the relative postcondition, while the preconditions of an action are changed by other nodes in the tree.

Following this representation, the LTM can be conveniently organized in JSON schemas. As shown in Listing 1, the root of a tree is identified by the key word root in its name (rbt_root). Actions simply are listed as children of a node and identified by the string \( A(\text{action\_name}) \). For preconditions, we use the notation \( C_{i,j} \) where \( i \) is the child number and \( j \) indicates the \( j \)-th condition. Postconditions (or goals) are identified by \( G_{i,j} \) where \( i \) is the child number and \( j \) indicates the \( j \)-th condition. It is worth noticing that the described representation contains all the information needed to instantiate an executable BT and that no further JSON schemas are needed to describe the leaves of the BT.

Listing 1. JSON schemas representing the generic RBT in Fig. 2.

```
{  
  "name":"rbt_root",
  "type":"fallback",
  "children": ["sequence_1"],
  "params": ["G_11", "goal reached"]  
},

{  
  "name":"sequence_1",
  "type":"sequence",
  "children": ["A(initialize blackboard)", "parallel_1]",
  "params": ["G_11", "blackboard initialized"]  
},

{  
  "name":"parallel_1",
  "type":"parallel",
  "children": ["A(handle priority)", "fallback_1]",
  "params": ["""]  
}

{  
  "name":"fallback_1",
  "type":"fallback",
  "children": ["A(load subtree)", "A(execute subtree)"]
  "params": ["G_11", "priority changed"]
}
```

The Instantiator is responsible for loading the task from the LTM and creating an instance of the BT to execute in the WM. This procedure is summarized in Algorithm 1. Given the task name (root of the BT), the Instantiator first loads the JSON schemas describing the task (line 2 in Algorithm 1). Starting from the root, the BT is built by iteratively expanding the nodes until the leaves are reached (lines 4 to 19). The current JSON schema is converted into the BT node specified in the type field and attached to the current tree (line 5). Pre- and postconditions are handled using a modified version of the Planning and Acting PA-BT approach in [2] that allows multiple postconditions. In this approach, a postcondition is transformed into a Condition node (line 11). In case of multiple postconditions, a Sequence node containing all the postconditions is sequentially verified. The case of a single postcondition is handled differently (lines 8–9). As for the postconditions, the preconditions are considered as Condition nodes (line 16). Action and Condition nodes are then connected to a Sequence node that is attached to the current tree (lines 17–18). In this way, an Action is executed only if all the preconditions are True. As a final note, the functions SEQUENCE(node) and FALLOUBACK(node) in Algorithm 1 return an empty subtree if the input is empty, while SEQUENCE(node), \( A \) returns the Action nodes \( A \).

D. Subtree priority

The modularity of standard BT allows a complex task (tree) to be decomposed into subtasks (subtrees). For instance, a stacking task can be decomposed as a combination of pick and place subtasks. However, in standard BT, the execution order of each subtask is predefined. Changing the execution order depending on discrete values is possible, but requires extra branches in the BT. Changing the execution order by monitoring continuous values like sensory data is typically not supported.

In contrast, RBTs exploit logical pre- and postconditions,
as well as continuous sensory data, to monitor the task execution. As already mentioned, a complex task is divided into subtrees. We assign pre- and postconditions to the root of each subtree. Therefore, a specific subtree is active if all the preconditions are satisfied while the postconditions are not. A subtree correctly terminates by setting the postconditions. At each tick, the Emphasizer accesses the blackboard and looks for active subtrees. An execution conflict occurs every time more than one active subtree exists. In this case, we exploit a priority-based mechanism to dynamically decide the subtask to execute. We define the priority of a subtree as the runtime prominence for the execution of a specific subtask. The priority is real value, normalized between 0 and 1, which tells the Instantiator which is the subtask to load and transform into an executable BT. In this work, the priority $\epsilon$ is defined as

$$
\epsilon(\theta) = \begin{cases} 
1 & \text{if } \theta \leq \theta_{\text{min}} \\
\frac{\theta - \theta_{\text{max}}}{\theta_{\text{min}} - \theta_{\text{max}}} & \text{if } \theta_{\text{min}} < \theta < \theta_{\text{max}} \\
0 & \text{if } \theta \geq \theta_{\text{max}}
\end{cases}
$$

where $\theta$ is a continuous value coming from sensory data, and the thresholds $\theta_{\text{min}}$ and $\theta_{\text{max}}$ are tunable parameters. In this work, $\theta$ represents the inverse of distance from objects to manipulate, but other choices are possible.

### E. Task execution and monitoring

The generic RBT, as the one depicted in Fig. 2, is a goal-oriented tree that successfully terminates only if a certain goal is achieved (the goal reached condition becomes True). In our implementation, the goal of the RBT is achieved if the postconditions of all the subtrees are satisfied. As already mentioned, the execution of the RBT is achieved by periodically traversing the tree top to bottom and left to right (tick function). At each tick, the goal reached condition is tested. If goal reached is False, we check that the blackboard is initialized and then enter a Parallel node. Executing the Emphasizer and the subtree in parallel is convenient because sensory data and task execution are, in general, asynchronous processes. The Parallel node is designed to successfully terminate if both children are successfully executed. Since the Action node handle priority is always in the running state, the Parallel node cannot terminate. This implies that the RBT successfully terminates if and only if the goal is reached.

If new sensory data arrive or a subtree postcondition changes, the Emphasizer recomputes the priority of the subtrees and sets the priority changed flag. This triggers the Instantiator that preempts the current execution, deallocates the current subtree, and instantiates the subtree with highest priority. As already mentioned, this branch of the tree—the branch inside the orange polygon in Fig. 2—is dynamically allocated at each tick. The dynamic allocation is needed for the correct execution of the task. To better understand this point, consider what happens if execute subtree returns True. In this case, the active subtree has been successfully executed and the Fallback node (fallback_1) also returns True (see Tab. I). With a static branch, the tick would not enter fallback_1 anymore, letting the remaining active subtasks unexecuted. With a dynamic branch, instead, the return state of fallback_1 is reset and the active subtree with highest priority is correctly instantiated and executed.

### IV. Evaluation

We evaluate RBTs in the sorting task shown in Fig. 3 where the robot has to pick 3 colored boxes (red, blue, and green) from a table (Fig. 3(a)) and place them at specific locations in a storage area (Fig. 3(b)). The scenario is simulated in CoppeliaSim [26] using the Panda robot model provided by Gaz et al. [27]. We consider two different case studies and compare the performance of RBTs and BTs in terms of execution time and tree complexity—the number of nodes in the tree. BTs are implemented using the open-source Python library py_tree [28]. RBTs are also implemented in Python exploiting the basic BT nodes provided by py_tree.

Figure 4 shows the BT used to plan box sorting subtasks. The solid nodes are in common between BTs and RBTs, and the thresholds are tunable parameters. In our implementation, the goal of the RBT is achieved if the postconditions of all the subtrees become True. In this case, the active subtask is correctly terminated and the Fallback node (fallback_1) also returns True (see Tab. I). With a static branch, the tick would not enter fallback_1 anymore, letting the remaining active subtasks unexecuted. With a dynamic branch, instead, the return state of fallback_1 is reset and the active subtree with highest priority is correctly instantiated and executed.
Fig. 5. The RBT used to plan the sorting task. In case study 1, sort box is endowed with preconditions to constraint the execution. The gray nodes are common to BTs and RBTs.

TABLE II
COMPARISON BETWEEN RBT AND STANDARD BT.

| Method | Case | # Nodes | Execution Time (ms) |
|--------|------|---------|---------------------|
| RBT    | 1    | 19 - 22 | 507.04 |
| BT     | 1    | 27      | 503.24 |
| RBT    | 2    | 19      | 505.17 |
| BT     | 2    | 151     | 819.78 |

dynamically attach the subtree in Fig. 4 to the static tree in Fig. 2. Moreover, the standard BT is endowed with 6 extra nodes (contained in the gray polygon in Fig. 2) to monitor the execution of the task and successfully terminate after a goal is reached. The task is fulfilled when all the boxes are sorted in the storage area, as indicated by the task goal G_11 = b_box placed \land g_box placed \land r_box placed. The thresholds used to compute the priority in (2) are empirically set to $\theta_{\text{min}} = 0.05$ m (the length of the box side) and to $\theta_{\text{max}} = 1$ m (the maximum distance that still allows to grasp a box). We compare RBT and BT in terms of number of nodes and execution time measured assuming that action nodes directly return True without entering the running state.

1) Case study 1: The goal of this experiment is to compare RBTs and BTs in a situation that favours the BT, i.e. when the task plan is rigid, no ambiguities are possible, and no external disturbances occur. In this case, we assume that the boxes need to be sorted with a specific order: first we pick and place the blue box b_box, then the green box g_box, and finally the red box r_box. This sorting order has been arbitrary decided and does not affect the obtained results. The sorting task successfully terminates when the task goal G_11 is reached. The BT used to perform the sorting task is shown in Fig. 6(a), where the 3 Action nodes sort box name compactly represent the BT in Fig. 4 (only the solid nodes are considered). As listed in Tab. II, the BT of Fig. 6(a) has 27 nodes. The RBT used to plan this task is shown in Fig. 5 and it is almost identical in the two case studies. The only difference is in the sort box Action node. In case study 1, we exploit preconditions (dashed nodes in Fig. 4) to impose a certain execution order. More specifically, the Action node sort box is allocated by the Instantiator that, at runtime, dynamically instantiates a specialized version of the sorting task where the generic box is replaced by the one with highest priority. As described in Sec. III-D, the priority of a subtask depends on logical precondition and continuous stimuli. In this case, external stimuli play no role and the execution order is fully determined by the preconditions. In particular, sort b_box has no preconditions and is the first to be executed. sort g_box has C_11 = b_box placed as precondition, while sort r_box has C_11 = b_box placed and C_12 = g_box placed as preconditions. This guarantees that the sorting task is executed with the desired sequential order. As listed in Tab. II, the RBT has a variable number of nodes (19 to 22). This is because the sort node has a variable number of preconditions for each.
box. Even if in case study 1 the RBT does not show its full potential, we still have a reduction of the number of nodes in the tree (22 nodes in RBT in the worst case, 27 in the BT). The time to execute the BT is slightly smaller in this case, but the difference is negligible (less than 4 ms).

2) Case study 2: This experiment is designed to show the benefits of the priority-based task execution introduced by RBTs. The scenario is the same case study 1 but here the boxes are sorted without a predefined order and the object closest to the gripper is sorted first. The RBT used to plan this task is the same of case study 1, except for the sort_box Action node that has no general preconditions. Therefore, the RBT always has 19 nodes (see Tab. II). At each time, all the boxes on the table are eligible to be sorted. These execution conflicts are managed in RBTs using the task priorities computed with (1). Hence, the Instantiator is free to allocate the subtree with highest priority, i.e. to start sorting the closest box. Once a box, for instance the blue one, is placed in the storage area, the postcondition b_box placed becomes True and the Emphasizer removes sort b_box from the list of active nodes (see Sec. III-D). This implies that sort b_box is not instantiated in future ticks, letting the robot sort the other boxes and successfully complete the task. In order to reach a similar level of flexibility with standard BTs, we need to complicate the control flow logic. A possible solution that requires 151 nodes is sketched in Fig. 3(b). In this case, RBTs require ≈ 85 % less nodes, which clearly makes the RBT easier to visualize, and a reduction of the execution time of ≈ 38 %.

V. CONCLUSION AND FUTURE WORK

We presented Reconfigurable Behavior Trees, a novel framework that combines high-level decision making and continuous monitor and control features. By combining the expressivity and modularity of standard behavior trees with the flexibility of attentional execution monitoring, RBTs allow the AI agent to perform actions in a robust and versatile way, while being capable of adjusting its behavior based on continuous input from the environment. The proposed framework has been tested in a sorting task and compared with standard BTs in terms of tree complexity and computation time. The evaluation shows that RBT outperform standard BT, especially when the task plan is not rigidly defined and ambiguities in the execution need to be solved.

In future work, we plan to test the RBT framework in human–robot interaction scenarios to cope with the uncertainties introduced by the human in the loop.

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