Automated Generation of Reactive Programs from Human Demonstration for Orchestration of Robot Behaviors

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Abstract—Social robots or collaborative robots that have to interact with people in a reactive way are difficult to program. This difficulty stems from the different skills required by the programmer: to provide an engaging user experience the behavior must include a sense of aesthetics while robustly operating in a continuously changing environment. The Playful framework [1] allows to compose such dynamic behaviors using a basic set of action and perception primitives. Within this framework, a behavior is encoded as a list of declarative statements corresponding to high level sensory-motor couplings. To facilitate non expert users to program such behaviors, we propose a Learning from Demonstration (LfD) technique that maps motion capture of humans directly to a Playful script. The approach proceeds by identifying the sensory-motor couplings that are active at each step using the Viterbi path in a Hidden Markov Model (HMM). Given these activation patterns, binary classifiers called evaluations are trained to associate activations to sensory data. Modularity is increased by clustering the sensory-motor couplings, leading to a hierarchical tree structure. The novelty of the proposed approach is that the learned behavior is encoded not in terms of trajectories in a task space, but as couplings between sensory information and high level motor actions. This provides advantages in terms of behavioral generalization and reactivity displayed by the robot.

I. INTRODUCTION

High-level behavior specification is the offline setup of information exchange between software components so that a robot performs autonomously a desired behavior online. Behavior specification of reactive behavior, i.e. development of programs that have robotic system operating in dynamic environments, while providing rich and engaging user experience, is difficult. To facilitate non expert users to program such behaviors, we propose a Learning from Demonstration (LfD) technique that maps motion capture of humans directly to a Playful script. The approach proceeds by identifying the sensory-motor couplings that are active at each step using the Viterbi path in a Hidden Markov Model (HMM). Given these activation patterns, binary classifiers called evaluations are trained to associate activations to sensory data. Modularity is increased by clustering the sensory-motor couplings, leading to a hierarchical tree structure. The novelty of the proposed approach is that the learned behavior is encoded not in terms of trajectories in a task space, but as couplings between sensory information and high level motor actions. This provides advantages in terms of behavioral generalization and reactivity displayed by the robot.

In this paper, we propose an algorithm to automatically generate Playful scripts from human demonstration (see Figure 1) starting from a set of motor primitives, i.e learning the list of statements setting the rules of activation of the robot primitives that will allow a robot to replicate the demonstrated behavior. The proposed algorithm is based on casting the identification problem in terms of inference in a Hidden Markov Model where the hidden states correspond to the activation of the set of primitives.

Playful is based on the reactive programming paradigm [2], i.e. the order of the statements in the script does not matter. Rather, at runtime, all rules of activation are continuously evaluated, and the motor primitives are activated or deactivated accordingly. Furthermore, the scripting language allows to group statements hierarchically to form new reusable higher-level primitives. This results in the implementation of behavior trees, in which activation status of branches are monitored online. Playful is further described in section III, in which an example of a Playful script is provided. Playful is available online [3].

Fig. 1. Overview of the proposed LfD framework: On the left motion capture is used to identify sequences of sensory-motor primitive activation using a HMM. On the right the resulting Playful script executed on the Pepper robot.

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the robot does not attempt to replicate the demonstrated behavior in all its modalities, which is often impractical considering the sensor and motor limitations of the average robotic system. Rather, it activates reusable primitives in a fashion that grasps the intent of the demonstrator, without the constrain of matching the richness, speed or ease of motion specific to humans.

In our experiments, we consider an interactive task where a human attempts to attract the attention of another human passing by, combining head and arm movements with walking. We consider elementary behaviors such as: walking toward (primitive) a human (target) when far from it (activation rule). The scripts, which are reported in the paper, are produced from a single demonstration and remain compact while capturing the essence of the task.

The advantages of the proposed approach are:

- Behavioral reactivity, due to the encoding in sensory-motor couplings,
- Possibility to amend the generated script by adding or removing statements; for example it is trivial to add a security behavior that has the robot safely shutdown when low in battery (see section \[\text{V}\]),
- Scripts can be generated from a single demonstration, as statements describe high-level actions applicable on large fraction of the task space (e.g. “go towards the human”).

It is important to note that the methodology focuses exclusively on first-order reactive and lively behaviors: it does not grasp higher-level planning, logical sequencing or reasoning from the demonstration.

After giving an overview of related work in section \[\text{II}\] we present further the Playful framework and formalize the problem of learning a Playful script from demonstration in section \[\text{III}\]. We then present the algorithm in section \[\text{IV}\] and some experimental results in section \[\text{V}\].

II. RELATED WORK

A. Behavior Trees

The execution of a Playful script implements a Behavior Tree (BT), which may refer to different concepts depending on the authors. In the Artificial Intelligence context, they are a specification of high-level behaviors that modularize in a hierarchical tree structure. In the video gaming industry, BTs have replaced finite state machines for encoding non player behaviors. In robotics they have been applied for high-level supervision of manipulation tasks [4], [5].

In a sense BTs are conceptually close to a Hierarchical Task Network, which have been extensively used for planning [6], but BTs implement dynamic behaviors which is closely related to supervision in robotic systems. In the Playful context, the engine reevaluates the BT at a fixed frequency, leading to activation and/or deactivation of its branches. This differs from the approaches in which logic is encoded in edges, and module activation relies on traversing the tree during operation [7].

B. Learning from Demonstration

Learning from human teachers [8], has been a subject of study of the robotics community for decades. It raises multiple questions, including how humans should convey the demonstration and how to design the learning algorithms [9]. LfD algorithms are generally classified along two dimensions. First, whether the policy is encoded directly or indirectly, i.e., Behavior Cloning (BC) vs. Inverse Reinforcement Learning (IRL). Second, whether the task is low or high level, i.e., task or motion control.

A lot of human behavior, especially long-term behavior, is related to higher-level cognition and planning, consider driving or navigating the internet. For such cognitive tasks that exhibit low dimensional action spaces in nature, IRL [10], has become state of the art [11]. IRL has also been recently extended to learn high dimensional control behaviors [12], [13]. IRL can identify the optimal criterion used when taking sequential decisions but is an ill posed problem that suffers from reward and policy ambiguity. Since our goal is not to plan for a sequence of actions, but rather activate sensory-motor couplings in a reactive manner BC applies in a more straightforward manner than IRL. Hence, our method is a type of BC using a reactive program to encode the behavior. We solve a high-level task, which can be related to encoding the selection of low-level options [14].

Hidden Markov Models (HMMs), have been used for BC of movement and activities and applied to many different domains including skill transfer [15], [16], sign language and gesture modeling [17]. Our approach is based on HMMs to infer the primitives that are active at each time step of the demonstration. Because our latent space remains small in dimension we can perform exact inference using the Viterbi algorithm.

C. Learning Behavior Trees from Demonstration

Despite the various works on learning from human demonstration, to the best of our knowledge work has been carried out on high-level orchestration. One exception might be found in [18], where a behavior based architecture is learned from demonstration. However, this work focuses on navigation behaviors and does not learn a reactive program.

III. LEARNING A PLAYFUL SCRIPT

1) Playful Framework: Playful is a software for the orchestration of robot behaviors. It allows developers to compose applications via a list of declarative statements such as:

\[
\begin{align*}
\text{head_search, priority of 1} \\
\text{targeting ball: look at, whenever seen, priority of 2} \\
\text{targeting ball: grasp, whenever close}
\end{align*}
\]

Listing 1. Playful grasping example

This playful script has a robot searching for a ball (line 1), looking at the one it detected (line 2) and attempt grasp when the ball is close to the robot (line 3).
Playful is based on reactive programming, i.e. the order of statements is of no importance, and no sequence of action is explicitly programmed. The three statements are continuously evaluated, and their primitives (here head_search, look_at and grasp) are activated when their evaluations (here, seen and close) return true. A priority is used to solve conflicts, for example head_search and look_at can not be active simultaneously because they share the resource head. Here, the higher priority of 2 for look_at takes precedence.

Evaluations, i.e. the activation rules, correspond to python code, e.g., close returns true if the distance between the robot and the ball is below a given threshold.

Playful scripts apply reactivity via the targeting keyword. A target (here “ball”) is a discretized sensory information item which data is continuously updated by the robot sensors. Targeting relates this data during runtime to the primitive it is associated with. In this example, this results in the robot moving the head to keep the ball in the center of vision.

Playful scripts encode behavior trees (see Figure 2) in which nodes may be primitives that correspond to python code communicating with the robot middleware; but may also correspond to other Playful scripts. For example, in the grasping scenario of Listing 1, grasp can be a Playful script consisting of two statements, move_arm and move_hand.

Thus, the status of evaluations and priorities results in the activation and deactivation of branches at run-time, shaping the behavior of the robot. For a complete formalized description of Playful, we invite readers to refer to [1].

2) Overview: Given a list of Playful primitives, we propose the automated generation of a playful script based on data collected during human demonstration. The approach consists of: • detecting in the human motion data the activation of the primitives • inferring from the data the evaluations related to these activation • learning the grouping and hierarchisation in these activations, i.e. the underlying tree structure • generating the script.

Next we formalize this learning problem.

3) Problem Statement: At the start of each learning from demonstration phase, the learner is given a set of observations (i.e., LfD dataset):

\[ D = \{x_t\}_{t=1:T} \]

which is a discrete time trajectory in \( X \). Elements of \( X \) encode positions and velocities of the humans and objects in the scene. Note that when recording high-level human activity in this way, the human action space is not directly mapped to the robot’s as typically assumed in kinesthetic demonstrations.

\[ \text{a)} \text{ Flat tree:} \quad \text{The state dynamics} \quad x_{t+1} = f_\theta(x_t, z_t) \]

resulting from the execution of a Playful script, can be expressed mathematically by the following function:

\[
 f_\theta^{(1)}(x_t, z_t) = \begin{cases} 
 a_1(x_t, z_t) & \text{if } e_{\theta_1}(x_t) > 0 \\
 a_2(x_t, z_t) & \text{if } e_{\theta_2}(x_t) > 0 \\
 \vdots & \text{if } e_{\theta_n}(x_t) > 0 \\
 a_n(x_t, z_t) & \text{if } e_{\theta_n}(x_t) > 0 
\end{cases}, \tag{1}
\]

where \( z_t \) is the Playful memory at time index \( t \), \( a_i \) is the result of the activation of the \( i \)-th leaf node (i.e., target-primitive association in each branch), and \( e_{\theta_i} : X \to \{0, 1\} \) are the binary conditional-evaluation maps parametrized by some vector \( \theta_i \).

We will subsequently call this representation, the flat tree, as it does not include any hierarchical grouping of nodes. Note, that we have relaxed the definition of \( f_\theta \) by leaving out the priority mechanism.

\[ \text{b)} \text{ Resources:} \quad \text{The simplified definition of a Playful behavior in Equation } \tag{1} \text{ only holds for the case where evaluations } e_{\theta_i} \text{ are disjoint. This is not the case in practice, however when the leaf nodes } a_i \text{ control a given resource, e.g., specific DoFs such as the arm, the base or the head, the actions are limited to separate dimensions of the range space of } f_\theta. \]

In this case, the flat tree can be expressed as follows:

\[
 f_\theta^{(2)}(x_t, z_t) = \sum_i e_{\theta_i}(x_t) a_i(x_t, z_t). \tag{2}
\]

c) Learning Loss: Given the priority simplification, learning a Playful script amounts to finding for each resource the parameters \( \theta \) that minimize the classic LfD mean squared-error loss:

\[
 L(\theta) = \frac{1}{T} \sum_t \| x_{t+1} - f_\theta^{(2)}(x_t, z_t) \|^2 \quad \forall x_t \in D. \tag{3}
\]

The overall behavior is the union of all flat trees found for each resource, and a hierarchical grouping of nodes can be performed based on activation pattern similarities of the leaf nodes \( a_i \). Note that there is always an equivalent flat tree corresponding to a hierarchical tree. The composition of a tree with several layers is beneficial to simplify the output script and provide reusable behaviors.

IV. ALGORITHM

Algorithm 1 sketches our method for Learning a Reactive Program from Demonstration (LRPD). Intuitively, the core of the algorithm can be viewed as being separated in the 3 flowing phases:

1) detect the most likely sequence of target-primitive activations based on a probabilistic inverse model,
Algorithm 1: Learning Reactive Program from Demonstrations (LRPD)

1) input: $\mathcal{D} = \{x_t\}_{t=1:T}$ sequence of observed states

2) begin

3) $O \leftarrow$ Compute target-primitive emission densities $p(o_t^i|w_t^i)$ for all time steps in $\mathcal{D}$;

4) for All resources do

5) $\mathcal{W} \leftarrow$ Find target-primitive activations using Viterbi on the HMM with emissions densities $O$;

6) $\Theta \leftarrow$ Train evaluations for active behaviors as binary classifiers over $(x_t, w_t^i)\in\mathcal{D}\times\{0,1\}$;

7) $\mathcal{T} \leftarrow$ Convert activations and evaluations $\mathcal{W}, \Theta$ to flat tree;

8) $\mathcal{T}_{\text{flat}} \leftarrow \mathcal{T}_{\text{flat}} \cup \mathcal{T}$;

9) $\mathcal{T}_H \leftarrow$ Find hierarchies in $\mathcal{T}_{\text{flat}}$;

10) script.pf $\leftarrow$ Convert $\mathcal{T}_H$ to Playful program;

In the following sections, we describe each of these steps.

A. Target-primitive Activation Detection

The first step of LRPD (i.e., line 3 and 5 of Algorithm 1), is to detect which target-primitive associations are active at each time step $t$ of our dataset $\mathcal{D}$. To do this we map the state space of an Hidden Markov Model (HMM) to activation patterns $w^i: t \rightarrow \{0,1\}$ at each time step $t$ of target-primitive associations $i$ (e.g., ball-grasp or ball-look_at in the example of Section III). We set uniform transition probabilities and model the observation $o_t^i$ probability at time $t$ of one such association by the following Gaussian emission densities:

$$p(o_t^i|w_t^i) \propto \exp \left( -\frac{|\phi_i(x_t^i) - \phi_i(x_t)|^2}{2\sigma_i} \right)$$

where $x_t^i$ is the state we would observe if the $i$th target-primitive was active. $\phi_i$ is some non-linear function of the state defined for the target-primitive $i$, (e.g., angular velocity when turning, heading direction when moving forward). $\sigma_i$ is a parameter of the algorithm. We make use of the Viterbi algorithm to recover the most likely sequence of activation $\mathcal{W}$ for all the combinations of targets and primitives.

B. Training of Evaluations Binary Classifiers

Once the data points $x_t$ are labeled with target-primitive activation $w_t^i$, evaluation functions $e_\theta$, can be trained to activate the target-primitive for each time index $t$. See line 6 of Algorithm 1. In general, any binary classification method could be used (e.g., support vector machine, neural network). However, in our experiments, we define a non-linear feature $\phi_d : X \rightarrow \mathbb{R}$, which models the human-robot interaction distance, and simply identify intervals of its range space.

C. Factorization of the Tree

The last step of the algorithm consists of unifying the flat trees $\mathcal{T}_{\text{flat}}$ defined for each resource and grouping the nodes in hierarchies. Grouping of nodes is performed by measuring similarity of their conditional evaluation functions $e_\theta$. Similarity between $e_\theta$ is difficult to define in the general case. In this work we simply compare the range space of $\phi_d$ and group nodes for which the interval bounds match with some $\Delta d$. This parameter trades off complexity for fidelity.

V. Example

We used the proposed approach to generate scripts that have a mobile humanoid robot (Softbank Robotics Pepper) applying strategies to attract passing visitors to a stand. Each demonstration was the result of capturing two humans (i.e., a demonstrator to mimic, and a visitor).

In this section, we provide implementation details, and show how the learned robot behaviors capture successfully the different strategies applied by the demonstrators.

A. Experimental setup

1) Robot: We made use of a Pepper robot from Softbank Robotics, which is 1.2 meters in height and offers a total of 20 DoFs, 17 for the body and 3 for the base (see Figure 4).

The base is omnidirectional and allows for holonomic navigation. Pepper is equipped with an IMU, which coupled with the wheel’s encoders, provides odometry. The odometry was used to update the position of the stand relative to the robot during all the experiments.

In this study, we used two of the three cameras available on the robot. The first is an RGB camera with a native resolution of 640*480 positioned in the forehead. The second is an ASUS Xtion3D sensor located in one of its eyes. We used these cameras in combination with OpenPose [20] for 3D human detection. The other sensors of the robot (sonars, infrared sensors, touch sensors and bumpers) were not used.

2) Available Playful Primitives: Previously and independently of this study, we implemented a set of basic Playful primitives for Pepper, which are listed in Table I.

Each primitive is associated with a resource, i.e., the robotic joint required for its activation. Primitives associated to the same resource may not activate at the same time. Because of the holonomic capabilities of the mobile base, wheels rotation and wheels translation refers to two separated resources.

Out of the eight primitives, four of them (turn_toward, go_toward, look_at and point_toward) have to be a associated to a target for activation. In this study, three targets are set to be tracked by the Playful backend: the visitor (human
For each resource, the most likely sequence of activation of target-primitive associations for demonstrator 1. Dotted squares present the grouping of target-primitives applied with a distance precision of 30 cm, as a preprocess for the generation of the algorithm presented in listing 3. A and B refer to the labeling of the resulting branches in the Playful script.

### TABLE I

**PRIMITIVE DESCRIPTIONS**

| Primitive   | Description                                      |
|-------------|--------------------------------------------------|
| resource: wheels rotation | turn toward | rotates body to face the target               |
|             | turn stop       | one minus angular velocity of the robot set to 0 |
| resource: wheels translation | go toward | moves toward the target, keeping a safety distance |
|             | go stop         | one minus velocity of demonstrator             |
| resource: head | look at | moves to keep the target object in the center of FoV |
| resource: arm | point toward | moves left arm to point toward the target       |
|             | waving          | waves the left arm                             |
|             | arm_freeze      | stops moving the left arm                      |

### TABLE II

**PRIMITIVE INVERSE MODELS (D IS DEMONSTRATOR)**

| Primitive   | Inverse observation model                                      |
|-------------|----------------------------------------------------------------|
| turn toward | angle between D body orientation and target velocity            |
| turn stop   | one minus angular velocity of D                                 |
| go toward   | angle between D position and D body-target vector               |
| go stop     | one minus velocity of demonstrator                              |
| look at     | angle between D head orientation and target velocity            |
| point toward| angle between D head-hand vector and D head-target vector      |
| waving      | velocity of D hand in the frame of his body                     |
| arm_freeze  | one minus velocity of D hand in the frame of his body           |

detected using the cameras), the stand and a virtual fixed position in front of it (tracked using odometry). This results in a total number of 16 possible primitives or target-primitives association that may be activated.

For the application of the algorithm presented in Section IV, an inverse models \( \phi_i \) for each primitive has been defined to implement observation probabilities \( p(o_{i,t} | w_{i,t}) \). Their mathematical formulations are reported in Table II. All \( \phi_i \) were normalized before training.

3) **Human demonstration**: Motion capture was performed using a Vicon tracking device (see Figure 4). Each dataset \( D \) captured the (fixed) position of the stand, the position of the visitor, the pose of the body of the demonstrator, the pose of the head of the demonstrator, and motion of the left hand of the demonstrator using a stick equipped with reflective markers.

Two participants (i.e, demonstrators) were recruited and given the instructions to try to attract a passing visitor to a stand. We required that he/she should 1) not touch persons or objects, 2) only use the left arm, and keep the right arm inactive and 3) apply common courtesy (e.g. not trying to attract to the stand by using physical constrain). Apart from these limitations, subjects were instructed to move freely in the experimental space. The subjects were not informed of the objective of the experiment.

The experimental space consisted of a corridor of 5 meters in length and 3 meters of width. The stand, a small pulpit, was located at the end and side of the corridor. The demonstrator starts at the stand, and waits for the visitor to enter the corridor. The visitor then enters the corridor, walking straight, before diverging toward the stand when at around 2 meters from it. During this sequence, the demonstrator moves freely. Data recording stops when the visitor reaches the stand, which occurs only a few seconds after the start of the demonstration phase.

The demonstrations are shown in the associated video \([4]\) at http://vincentberenz.is.tuebingen.mpg.de/videos/automated_playful.mp4. It can be seen that the two demonstrators apply different strategies. Demonstrator 1 goes in front of the stand while actively pointing towards it. Demonstrator 2 goes toward the visitor before backing toward the stand.

4) **Algorithm run**: Algorithm 1 was applied, computing the most likely sequence of activation of target-primitive association. This computation took less than a second on a regular office desktop. The output for demonstrator 1 is represented in Figure 3. From right to left (decreasing distance between the visitor and the stand), it can be seen that the demonstrator first walked to the front of the stand (green color) while turning toward and looking at the visitor.
go_stop, whenever d in [2.1,2.5]
targeting stand: go_toward, whenever d in [0.6,2.0]
targeting visitor: A, whenever d > 2.7
targeting intercept: go_toward, whenever d > 2.7
arm_freeze, whenever d > 4.7
waving, whenever d in [2.9,4.6]
targeting stand: B, whenever d < 2.7
A:
  turn_toward
  look_at
B:
  point_toward

Listing 2. Script generated from the demonstration of demonstrator 1. d refers to the distance between the visitor and the stand.

go_stop, whenever d > 4.8
targeting visitor: go_toward, whenever d in [3.2,4.6]
targeting stand: go_toward, whenever d in [0.7,3.0]
targeting visitor: A, whenever d < 5.1
arm_freeze, whenever d > 4.2
targeting client: pointing_at, whenever d in [0.8,3.7]
A:
  turn_toward
  look_at

Listing 3. Script generated from the demonstration of demonstrator 2.

(red color); and waving the hand (violet). As the visitor approached, the demonstrator started to redirect himself toward the stand while pointing at it (blue color). From this sequence, overlapping target-primitives are then grouped together using a similarity score implementing a tolerance of 0.3 meter (dotted squares in 3). These groups, labeled A and B, corresponded to branches in the subsequently generated Playful scripts. Related evaluations $e_\theta$ consisted of the boundary in terms of distance between the visitor and the stand observed during activations.

The resulting Playful script is shown in Listing 2. It encodes this demonstrated behavior. For example, when the visitor is far (distance superior to 5.1), the branch A activates targeting the visitor, i.e. the robot is commanded to turn toward the visitor while looking at it (line 3). Similarly, when the visitor gets closer (distance below 2.7), the branch B activates, commanding the robot to look at the stand while turning and pointing towards it (line 7).

The same procedure was applied for demonstrator 2, resulting in Listing 3. This script reflects the different strategy applied by the second demonstrator, for example first approaching the visitor (line 4) before backing toward the stand (line 3).

5) Implementation and result: To the generated Playful script were added two nodes:

- A higher priority security node, that has the robot safely deactivating itself when its battery is low, or its head is touched
- A lower priority default behavior node, that has the robot moving randomly the arms and the head, while going back to the stand. This node provides a default simple set of primitives that activate when the visitor is not detected.

The generated scripts were not edited in any other way, and directly executed on the robot, as shown in figure 4. The resulting behaviors can also be seen on the support video.

The behavior of the robot and of the demonstrators only look loosely alike from an aesthetic or in regards of dynamic trajectories executed, which is to be expected considering 1) the sensor and motor limitation of the robot and 2) the simplicities of the primitives the human demonstration were mapped to. But it can be clearly observed that the robot replicates with fidelity the high level strategy of each demonstrators as described in the previous section V-A.4.

Fig. 4. Pepper robot attempting to attract a visitor to a stand by running a script generated from human demonstration
VI. DISCUSSION AND FUTURE WORK

The method proposed in this paper introduces an important first step for combining expert and novice ways to program reactive robotic behaviors. It does so by allowing a novice to intuitively make use of a set of primitives provided by an expert.

LfD is notoriously difficult due to the mismatch in sensory-motor capabilities between the human demonstrator and the robot. In this context, a vast amount of previous work has focused on the retargeting problem of learning low-level skills, but the problems due to mismatch in sensor capabilities have been largely overlooked. This is a particularly limiting factor when mapping reactive behaviors. For instance in our experiments, the human was easily getting out of the field of view of the robot. Our framework alleviated this issue by allowing the expert to easily inject small modifications (implementation of a default behavior node) accounting for limitations which he/she encounters at run time, thanks to the encoding of the behavior in a high-level programming language.

However, we report a few limitations to our current framework. Our implementation was based on a single non linear feature (section IV-B), which would be insufficient for more complex scenarios. Using higher-dimensional feature spaces will pose the question of the relevant features to take into account. To avoid this issue a possibility would be to learn evaluations end-to-end from the raw kinematic states directly, which would pose the question of the similarity measures to use when comparing evaluation functions encoded with non-linear function approximators.

Finally, the present work only explores an implementation of first order reactive behavior, which poses an important limitation for extending this framework to life-long learning. In such a scenario learning to perform complex tasks where planning is required is key. We are currently investigating the first step in this direction, which interfaces reactive programming in Playful with symbolic planning.

VII. CONCLUSION

In this paper, we have presented an algorithm that mixes expert and novice knowledge for automatically generating Playful scripts which encode reactive behaviors.

The proposed algorithm detects the most likely sequence of active motor primitives by inference in a Hidden Markov Model. To this end inverse models of the primitives have to be provided and we have proposed such a model for 8 primitives in our experimental section. Further hierarchical Behavior Tree structure of the active sensor-motor couplings directly maps to a Playful script.

We have tested the effectiveness of the approach on an interactive task where a demonstrator attempts to attract the attention of a passing visitor. The scripts, learned from a single demonstration, remained compact while capturing the essence of the task.

VIII. THANKS

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