Automated acquisition of structured, semantic models of manipulation activities from human VR demonstration

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Abstract—In this paper we present a system capable of collecting and annotating, human performed, robot understandable, everyday activities from virtual environments. The human movements are mapped in the simulated world using off-the-shelf virtual reality devices with full body, and eye tracking capabilities. All the interactions in the virtual world are physically simulated, thus movements and their effects are closely relatable to the real world. During the activity execution, a subsymbolic data logger is recording the environment and the human gaze on a per-frame basis, enabling offline scene reproduction and replays. Coupled with the physics engine, online monitors (symbolic data loggers) are parsing (using various grammars) and recording events, actions, and their effects in the simulated world.

I. INTRODUCTION

We are currently seeing fast progress of robotic agents learning manipulation tasks [1], in particular through imitation [2] and reinforcement learning [3]. However, in many cases the amount of experience needed for learning exceeds what can provided with reasonable effort [4], in particular if a single experience corresponds to a complete manipulation episode. One way of reducing the number of experiences needed for learning is to increase the information content of an episode. This can be achieved by transforming experiences into appropriately structured activity models and interpreting episodes by applying structural and teleological, as well as causal and intuitive physics knowledge to them. While several approaches are starting to look towards this direction [5] we believe that there is much higher potential in such activity representations as human activities are highly structured and have many regularities [6], [7] that have been investigated thoroughly in an interdisciplinary research field called action science [8].

In this paper we advance the acquisition of learning data from human virtual reality demonstrations by building on top of our previous work: AMEvA (Automated Models of Everyday Activities) [9], [10] – a special-purpose knowledge acquisition, interpretation and processing framework, capable of recording and detecting force-dynamic states of manipulation activities performed in virtual environments. The main limitations of the previous system were the coarser representations of the human models and their actions. The human model was consisting of only the head and hands, tracked by the VR headset and the two controllers. This approximation implies that we can only get trajectory data of the hands and the object manipulated by the hand but not full-pose data of the human body. Also, the model allows the human to reach locations that are impossible to reach in reality because other body parts would collide with the environment, or cannot use various body parts to manipulate the environment, for example closing a drawer or a door using an elbow or a foot.

As a result, the contributions of this paper are: (a) the improved human model representation; (b) a more realistic interaction with the virtual world; and (c) the granularity of the action and event recognition/segmentation; For (a), we integrated gaze and full body tracking systems to provide us in depth access to the human motions and intentions. The virtual human body obtained an in-depth semantic representation for its skeletal body parts using KNOWRob [11], thus commonly shared with the robot. This was done by extending the upper ontology with classes, properties and relations of the virtual body parts. In (b) the primary interaction advancement is a fully physics-based grasping model, where grasping occurs as a result of opposing forces and friction applied to an object through the hand parts. The integrated full body allows, as previously mentioned, for more natural and complex
interactions, such as closing doors/drawers using other body parts than the hands (elbows, foot). For (c), the main contribution is the implementation of more granular online monitors capable of detecting and segmenting generic, physics-enabled interactions. We extended the Flanagan model [12] for pick-and-place being able to robustly detect reach-to-grasp (prehension) movements such as reaching, fixation, grasping, sliding, picking-up, transporting, putting-down.

Figure 1 partially illustrates the aforementioned contributions by depicting a segmented pick-and-place action into meaningful motion patterns (top) and the gaze of the human during the same execution (bottom). The scene is reproduced at the start of the reaching motion and annotated with colored markers (hand trajectory and human pose) for each following motion phase. Red for reaching, yellow for fixation, green for picking-up, teal for transporting and blue for the putting-down motion.

The remainder of the paper is organized as follows: Section II gives an overview of the framework, describes the symbolic virtual environment and the structure of the episodic memories connected with the robot’s knowledge base. Section III presents the interaction of the human with the virtual environment. Section IV introduces the online activity recognition modules and their heuristics. Section V introduces example queries for accessing the experiments data from the hybrid knowledge base. We introduce various related works in section VI, and conclude in section VII.

II. OVERVIEW

Figure 2 depicts the overview of the system, where a user is asked to perform a task in a virtual environment. The environment is connected to an extended KNOWRob knowledge base, which includes the representation of all the entities and their properties in the virtual world (humans, objects, lights, articulations, partonomies), as well as the actions and events which can occur during the task execution. A subsymbolic, and symbolic, logger is running in the background, recording on a per frame basis every change in the environment (including human gaze), where the latter is a collection of modules capable of detecting and recording actions and events. These are then indexed and stored in a hybrid knowledge base in the form of episodic memories.

A. Virtual Environment

The data structure used in the virtual world can be split into two categories: “materialized” and “abstract” entities. These can further be categorized as relevant for the rendering engine, the physics engine, for both, or for none. The “materialized” entities are the ones that can be drawn by the rendering engine and simulated by the physics engine: the human body (skeletal body), the objects in the environment (rigid bodies) or physics-based particles such as liquids or soft bodies. “Abstract” entities, such as lights or visual effects particles (sparks, flames etc.) are only relevant for the rendering engine, whereas joint/spring entities are only relevant for the physics engine. Custom abstract entities such as gaze pose are irrelevant for both, since they are not simulated nor rendered. Depending on their types, the entities have various properties, such as collisions, mass, friction parameters, textures, etc. for “materialized” entities. Emitted light color, intensity, shape, etc. for lights. Motion limits (prismatic/linear), damping, stiffness coefficients, etc. for joints. Another important property is the partonomy relationships between the entities, for example that the drawer handle is part of the drawer. For each entity and property there is a corresponding representation in the extended ontology of KNOWRob.

B. Episodic Memories

The right side of Figure 2 depicts the structure of the logged datasets. It is split into a symbolic and subsymbolic representation. The symbolic part is stored in KNOWRob and represented using OWL [13], whereas for the subsymbolic part we are using MongoDB databases. Examining the dataset from top to bottom, we first have a number of tasks stored using a KNOWRob instance bundled with a MongoDB server. A task represents a virtual environment scenario where users are given a specific assignment. Tasks are concepts in the ontology, where each new task is represented as a unique instance in the knowledge base and a separate database in MongoDB. Such a task example would be to: "set the table for dinner", "clean the table after breakfast", or "put the dirty dishes in the dishwasher". Each task component is split into two
parts: the metadata, which stores the data at the task level, and the episodes collection, which are the instances of every executed tasks. The concept of “episode” is also represented in the ontology, therefore every episode instance will receive a unique identifier at instantiation, thus allowing KNOWRob to classify each occurred event per episode and to query the knowledge base as a whole.

The symbolic section of the metadata represents the instantiation of every entity class from the virtual world, which entails: generating unique identifiers using UUID’s for each entity, thus guaranteeing uniqueness of all the instances across any previous or future tasks; and collecting all properties of the entities. The subsymbolic section stores all the binary assets required for the virtual environment to re-build the task scenario: meshes, materials, textures, shaders, lighting builds of the map, etc. These are stored using MongoDB’s large files management system gridfs.

At the symbolic level each episode stores all the events, actions and their effects that occurred during the task execution, these are stored into per episode separate OWL files. At the subsymbolic level, for each episode a new MongoDB collection is created, storing the world states on a per-frame basis and the gaze information. Since the database is no longer altered after the episode completion, this allows us to optimize the database for fast querying using multiple indexes. Every relevant field will be indexed and internally organized as a B-tree data structure, thus reducing the search time complexity to $O(\log n)$.

III. INTERACTION

In this section we present how the mapping of the human movements onto the virtual avatar is implemented. In order to interact with the environment we are using three types of interactions. First, we have the full body tracking data applied to the virtual human body as an animation. Second, a more refined controller is used for the hands movement, allowing for a more precise fine-tuning to approximate real world conditions. Finally, we have a physics-based grasp system capable of switching between various predefined grasp styles. With the three interactions styles the user gains full control over its virtual movements, giving him/her the freedom to move in the open world as naturally as possible.

A. Full Body Tracking

The full body tracking system is currently a live animation, meaning it will map every received bone position from the tracking software to the avatar, neglecting the environment. Basically, it can apply forces to the environment, but it cannot receive any feedback. Thus, if willing, the user could cause instabilities in the simulated world by walking through walls or furniture. Although the limitations, the user can still take advantage of the additional limbs to interact with the world, and will force him/her to use natural movements when doing so.

B. Hand Control

In order to have a more close-to-reality interaction, we needed to use a different approach for the parts predominantly used to interact with the world, namely the hands. A direct mapping would have made the interaction most reactive, it however would also cause the user to interact with objects as they would have been weightless. We therefore implemented an approach to allow a two-way interaction with the world. When lifting a heavy object, the object would pull back on the hands, or slip out. This would compel the user to use strategies to interact with the environment, as it would in the real world, such as using two hands for stabilizing objects, or for lifting heavier ones. For the implementation we used two 3D PID controllers, one for the translational motion and one for the rotational one. The controllers are in a closed loop with the tracking system, from which they receive the 6D target pose and then apply forces and torques to the hand to try to move it to the desired pose. The controller parameters gives us the possibility to calibrate the hands in order to match close to real world values in terms of responsiveness and strength.

C. Physics-based Grasping

In order to have plausible action effects during the task execution we implemented a physics-based grasping model on top of the simulated hands. We have chosen the most common grasp styles for everyday object manipulation and classified them according to Feix et al. [14]. The grasp styles were created using standard 3d animation tools, where each grasp consists of multiple frames storing the joint state information of the skeletal hand. The left part of Figure 3 shows an example of three grasp styles (top to bottom: pinch, wrap and tripod) and some of their frames as waypoints. These animations are then stored in into “physics grasp animation” datasets which are loaded by the grasp controller. The controller will therefore react to two user inputs: a discrete one, which changes the grasp style; and an analog one, which interpolates the button mapping between the grasp animation frames, resulting in the target angle for the joints.

![Fig. 3. Physics-based grasp animations (left) and contact sensors (right)](image)

To control the bone movements, each joint is equipped with a driver, which takes as input the interpolated value from the grasp animation. Torques are then applied to
move and maintain the joint at the given angle. The drivers operate similar to a PD controller using two inputs: stiffness and damping. Where stiffness controls the strength of the drive towards the target joint angle, and damping towards the target velocity. In other words the strength of executing the grasp and the strength of maintaining the grasp pose from any external perturbation.

![Image](image_url)

**Fig. 4.** Naïve physics reasoning capabilities

In Figure 4 we showcase the real world plausibility of the physics-based interaction systems. We depict a timeframe of picking up a filled plate using a lateral grasp style with one or two hands. We notice on the top timeframe during the pick-up motion due to its weight the plate twists out of the grasp. However, using two hands, the weight is distributed among two points, thus greatly reducing the twist force applied by the plate, resulting in a successful pick-up. Such events can provide robots with naïve physics understanding of their actions. Having the grasp styles represented as concepts in the ontology, it will also provide the robot with a mapping between grasp styles and objects, or actions.

IV. Online Activity Parser

In the following section we present the online activity and event detection modules running in realtime during the task execution and symbolically record the various events occurring in the virtual world.

A. Grasp Detection

As described in the previous subsection III-C the current grasping model is physics-based, therefore, even though we have the user's intention to grasp something, the actual success of the action depends on the surrounding environment. In order to differentiate between a contact with the hand while grasping and an actual grasp event, we equip the virtual hands with arrays of contact sensors (see right side of Figure 4) to detect if the user has something in the hand while executing the grasp animation. The contact arrays are grouped into different sets, in the example image we have green for the finger bones (phalanges), red for the thumb, and blue for the palm (carpal bones). The grasp detector module is only activated when the user starts the grasp animation. The module is then keeping track of all the objects in contact with the sensors in the sets. A grasp is detected when an object is in contact with sensors from at least two different sets. Having the sensors covering most of the hand area, it can can also detect grasping multiple objects simultaneously.

The module will not differentiate between the grasping contexts, for example, grasping an object to be transported, a handle to open a drawer, or grasping an unmovable object such as the furniture. It will regardlessly semantically annotate, and record the occurred grasping event containing: the start and end time of the event, the hand and the grasped object instances, including the grasp style used for performing the action. Using KNOWRob these events can further be particularized, using first order logic rules to infer grasps related events such as “grasping onto” or “holding onto” if during the grasping event the “acted on” instance has a mass larger than the strength of what the grasping hand can handle.

The grasp detection system is susceptible for different grammars for detecting grasps, it can handle more than three sets of sensors array if required. For examples if one would like to detect lateral finger grasps (these however are very uncommon in a kitchen environment), one could add for each finger a different set of sensor array.

B. Contact and Supported-by

One of the building blocks for detecting force-dynamic events are the contact and supported-by events [15]. In our framework the two are bundled together in one module which is equipped on every object in the world. Tightly coupled with the physics engine, the module will subscribes for any collisions occurring on the object. When a collision is triggered, it is interpreted into a semantic contact event, and it starts checking for supported-by event until the contact finishes. The grammar for checking for the supported-by event requires that the two objects in contact have a relative vertical velocity of close to zero. This way if an object is being transported on a tray will still be detected as supported-by the tray.

Being tightly coupled with the physics engine, the modules are only active when the objects are simulated. For optimization reasons the physics engine disables all objects that are in a stable state, when this happens, the modules are also deactivated. This way the system can scale to support thousands of objects without effecting the real-time performance. Once an object is being simulated again, the corresponding module is re-activated and continues listening for events.

In the left side of Figure 5 we show an example of detecting contact and supported-by events between two objects and a supporting surface. The yellow ellipsoid areas represent contact events, whereas the green ones supported-by.

C. Extended Pick-and-Place Detection

Building upon the aforementioned modules, we now introduce the grammar used for detecting and segmenting...
Fig. 5. Key frames of the activity parsing grammar

a pick-and-place action into relevant motion patterns. Figure 5 depicts the most significant stages used by the grammar to detect the reach-to-grasp action (top) and transport with placing (bottom).

For every pick-and-place action we first start detecting the *reaching* motion, which is an important motion pattern for any robot control system executing manipulations tasks. In our model, reaching represents: the motion of the user’s hand towards an object which will eventually be grasped. The reaching motion is finished when the hand (contact sensors) are in contact with the to-be-grasped object. The starting point for reaching is hard to detect because there are no distinct features for such motions. Our current solution is to approximate this with a region of interest in front of the hand. In image (a) we can see the depiction of a reaching motion. We have in the scene three objects which are supported by a surface. A gripper, representing the human hand, and the region of interest in front of the hand. Whenever an object overlaps this region of interest, it will be marked as a potential object-to-be-reached, the occurrence timestamp will be saved, and its relative distance to the hand will be tracked. In the depicted image the three objects are all overlapping the region of interest of the hand, where the blue stars represent the moments when the objects are marked as a reach-to candidate.

In the next image (b) we showcase two main happenings: firstly, (♦) the start of a potential *fixation* action, directly causing the end of the related reaching motion (still potential). Fixation represents in our system: the movement of the hand—while in contact with the to-be-grasped object— to the desired grasp pose, however, not every reaching motion needs to be preceded by a fixation. In the image the contact between the hand and the potential object is shown by the small yellow ellipsoid area. Secondly, (♦) we drawn the trajectory of the hand from its previous pose until its current one. The trajectory is split into two colors: a green one, representing the reaching trajectory, and a gray one which would have been the theoretical starting point for a reaching motion, if the previously mentioned rule would not had been broken, namely: “the motion of the user’s hand towards an object”.

At one point the hand was moving away from the objects, thus the start-to reach time of the tracked objects was being constantly reset until the hand started moving back towards the targets again. In the image we can notice the apple is no longer in the region of interest, however the milk carton is is. The model is still keeping track of the objects in the region since it cannot know the intention of the user, it might not grasp the object.

In image (c) the user grasped the object (grasp contact points shown in red). During the grasp the region of interest in no longer required, and the cached potential objects are removed. The hand trajectory is extended (shown in blue), representing the hand fixation motion pattern. After grasping the object there are two possible motions that can follow: (d) *slide* or (e) *pick-up*. We define a sliding motion: a voluntary motion of a grasped object on its supporting surface. The sliding motion in the example frame ended when the object contact with its supporting plane ended. This could mean that the object was either picked-up or directly transported. In the example image, the object goes directly in the transport state. The sliding trajectory is depicted in purple. The other possible case is a pick-up motion, defined as: lifting a grasped object off its supporting surface. Similarly as in the reach motion, pick-up does not have any distinct features to segment it. We know it starts when the contact with the supporting surface is broken, but cannot tell when it ends. For example, when picking up an object off the floor and placing it on the top cupboard, it is hard to tell when the pick-up motion becomes a transport motion. For this we wen with a similar approach to reaching, when the contact with the supporting surface is broken, a region of interest is created, and when the grasped object leaves this area, the pick-up motion is marked as finished. In the image the trajectory is depicted in yellow, and the leaving of the region of interest with a purple star.

The following motion is *transport*, and it is depicted in figure (f) and (h). This is defined in our grammar as: the motion of a grasped object after a slide or pick-up, until either released, or a put-down or a sliding motion occurs.
In (g) we can observe a transport motion followed by directly by sliding. This happens if the grasped object is not approaching the supporting surface from above. If the object is approaching the supporting surface from above, a put-down motion will occur. We know this ends when the object is in contact with the supporting surface, however, we do not know when did it start. For this reason during the transport motions we cache the movements of the grasped object with a decay time, we illustrated this in the images using a green transparent line beneath the hand trajectory. The approach now becomes, whenever a put-down motion happens after the transport, a region of interest area is created and we backtrack the motions of the grasped object until it stops overlapping this area, we then mark this as a start point of the put-down action. We depicted this situation in image (i). Similarly as in the the reaching case, if during the put-down motion, the object is moving away from the supporting surface, the put-down motion is cut short, starting only when there was a continuous approaching motion towards the target. This case is depicted in image (j).

V. EXPERIMENTS

In the following section we briefly present a few shortened KNOWROB [11] query examples on how specific data can be accessed and visualized from the hybrid knowledge base, the results are visualized in Figure 6.

In the first example we ask for directly detected events, without having any specific reasoning. The query boils down to searching for a given action type acted on a given object type. After a result is found, the action timestamps and the object instance are used to reconstruct the world at the given time and append the queried markers to it. The results can be seen in the top left part of the figure.

In the following query we take advantage of the partonomy representation of the world in order to narrow down our search for specific objects. In this case we are querying for grasping handles belonging for specific classes. We can see the results visualized in the top right side of the image.

In the final query we are using sub-actions to define an upper action type. In our case a pick-and-place action, which is not directly detected by the system, only their subparts. Rules are defined on which sub-actions belong to the type, and their order can be specified using temporal reasoning [16].

VI. RELATED WORK

Similar to our approach, in [17] the authors present a similar system with the scope of collecting automatically annotated synthetic data from virtual environments, focusing mainly on visual realism. In comparison the human interaction in our system is physics based, is capable of automatically detecting and annotating actions and events in a robot understandable manner.

In [18] the authors use a dataset of human activities executed in a virtual reality environment to generate hypotheses about casual dependencies between actions. A consolidation of the two system would allow the possibility to collect and access labeled human activities without the need of manual annotation.

VII. CONCLUSION AND FUTURE WORK

In this work we presented a framework able to automatically collect fully annotated motion data from virtual environments. The data is stored in a hybrid knowledge base, combining symbolic and subsymbolic representation, understandable and accessible by robots. For the virtual environment representation we are using Unreal Engine 4 with its underlying physics engine NVIDIA PhysX.

As future research, we are planning to implement various improvements to the system, such as avoiding one directional physics on the animated human body, integrating a refined physics interaction similar to the hand controllers. As a first step would be to use blended animations, which has the capability to follow the tracked body animation and to react physical interference. We would also like to use human gaze patterns in order to refine the action detection heuristics, especially in cases where there are no other cues to use. Another objective is to collect a large scale dataset similar to epic kitchen [19] and have it available online for robots and researchers via the OPENEASE[20] platform.
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