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Knowledge Base Representation for Humanoid Robot Skills ⋆

Daniel Hernández García, Concepción A. Monje, Carlos Balaguer *

* *Universidad Carlos III de Madrid. Robotics Lab. Department of Systems and Automation Engineering. Av. de la Universidad 30, Leganés, Madrid, Spain. 28911. (e-mail: {dhgarcia, cmonje, balaguer}@ing.uc3m.es*

Abstract:
The ultimate goal for humanoid robotics research is to develop humanoid robotic systems capable and flexible enough to handle the challenge of working alongside human in complex natural environments performing everyday tasks. To reach this goal it is key to develop appropriate structures in which to organize the acquire knowledge in a manner that allows the system to retrieve it in order to use it to fulfil its missions. In this work a knowledge base representation of the robot skills knowledge organized in terms of the relationships between objects, actions and event frames is proposed.

1. INTRODUCTION

Great advances have been made in humanoid robotics research, especially during the last two decades. There currently exist robots that walk, run or climb stairs, that can handle and manipulate objects, that interact and play games with people, etc. However, all this robots exist in the scope of research departments of universities or technological companies. Despite all advances, the ultimate goal of an intelligent and autonomous humanoid robot companion is still far from reach. Important challenges remains to be solved. Functional humanoid robots would need to execute a wide range of movements in a natural human-like manner. They would also need to process information from multiple sensors into a reliable representation of the world in order to understand and react to their environment. Also, they must be engaging and responsive, and they must present intelligent, natural and predictable behaviours.

In this work we focus on the challenge of providing robots with systems that allow them to continuously learn new skills knowledge and adapt their existing skills knowledge to new contexts. The aim is to build knowledge base with the knowledge of learned skills allowing for its storage, classification and retrieval, for a humanoid robotic systems to be able to access its acquired knowledge in a manner that allows it to retrieve it in order to use it to deal with the constraints and conditions of its current context.

Section II surveys related work on libraries and knowledge base of robot skills. Section III address the framework for learning the skills. Section IV discuss the knowledge representation formalism. Section V presents the structure of the knowledge base. Section VI concludes this paper.

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2. ROBOT SKILLS KNOWLEDGE LIBRARIES

Main goal for humanoid robotics research is to build human like robots that can work with humans in continuous changing environments and performing a wide array of tasks. To achieve a complex behaviour such as this it would be necessary to have inclusive and comprehensive repertoires of skills. For this the concept of movement primitives, also called movement schemas, basic behaviours, units of actions, etc, is important. Movement primitives are basic sequences of action accomplishing complete goal-directed behaviors (Schaal [1999]). Coping with the complexity of motor skills learning for robots, needs to rely on the insight that humans decompose motor skills into smaller subtasks. Many theories about motor primitives suggest that they are viable means for encoding humanoids movements.

The movement primitives are sequences of action that accomplish a certain movement goal. The primitives encode groups or classes of stereotypical movements (Mataric [2000]). To deal with complex motions a library of movements primitives can be built (Pastor et al. [2009]), providing basic components from which multiple desired robot tasks can be performed by combination and superposition of the primitives. A robotic system equipped with a well stock library of movement primitives can be though of possessing an adequate repertoire of actions to deal with a vast range of situations. Such collection of primitives are used to build a knowledge base from the learned motions of a task. Various examples can be found on building up knowledge base from learned motion tasks.

The work of Ijspeert et al. [2003] suggested using dynamical systems (DS) as motor primitives. Control policies could be used to represent basic movements that form a library of motions. Defining the primitives in term of causal dynamical systems allows then to be parametrized by a small set of dynamical parameters and an input driving the overall dynamics.

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Mataric [2000], proposed to structure the motor system into a collection of movement primitives, which then serve both to generate a movement repertoire to the humanoid robots, and to provide prediction and classification capabilities for visual perception and interpretation of movement. The movement primitives represent the generic building blocks of motion that can be implemented as parametric motor controllers.

Zoliner et al. [2005] built up a knowledge base of tasks by extracting relevant knowledge from demonstrations of manipulation problems. They dealt with the integration of learned tasks into a knowledge base as well as enabling the system to reason and reorganize the gathered knowledge in terms of re-usability, scalability and explainability of learned skills and tasks. Goal was comparing newly acquired skills with already existing tasks knowledge and deciding whether to add a new task representation or to expand the existing representation with an alternative.

Ude et al. [2007] presents a framework for synthesizing goal-directed actions from a library of example movements, different methods can be utilized for the construction of this movements library. The approach used a general representation based on fifth order splines.

In Pastor et al. [2009] a collection of dynamic movement primitives is used to build a library of movements by labelling each recorded movement according to task and context. Their work provides a general approach for learning robotic motor skills from human demonstration. Generalization can be achieved simply by adapting a start and a goal parameter in the equation to the desired position values of a movement.

In Muelling et al. [2013] the goal was to acquired a library of movement primitives from demonstrations and to select and generalize among these movement primitives to adapt to new situations. The primitives stored in the library are associated with a set of parameters that form an augmented state that describes the situation present during demonstration and are used as components in a mixture of motor primitives algorithm.

Representations of robot skills must be flexible and compact enough to store, use and retrieve this knowledge in efficient ways and let the robot have a comprehensive repertoire of skills. Motor controller components of the movement primitives could be manually derived or learned. The learning of movement primitives would benefit from coding the complete temporal behaviours that result in state-action representation that are compact and which need to adjust only a few parameters for a specific goal (Schaal [1999]). In this work a framework to build the models of the robot skills using *Learning from Demonstration* techniques was chosen to learn the robot skills.

3. ROBOT SKILL LEARNING

The *Learning from Demonstration* approaches focus on development of algorithms that are generic in their representation of the skills and in the way they are generated. One of most promising approaches are those that encapsulate the dynamics of the movement into the encoding, (Billard et al. [2008]). Autonomous dynamical systems (*DS*) has been proposed representing movements as mixtures of non-linear differential equations with well-defined attractor dynamics (Ijspeert et al. [2001]). The *DS* approach could also be use to exploit its representational properties for movement generalization, recognition and classification (Pastor et al. [2009]). *DS* can create a rich variety of non-linear dynamics models fitted for point attractor and limit cyclic systems allowing encoding of both discrete and rhythmic movements (Ijspeert et al. [2009]).

3.1 Learning Motion Dynamics as Multivariate Gaussian Mixtures

The *DS* framework provides an effective mean to encode trajectories through time-independent functions that define the temporal evolution of the motions. The motion dynamics are estimate through a set of first order non-linear dynamical system equations. It is assume that the motion is governed by a first order autonomous ordinary differential equation,

$$\dot{\xi} = f(\xi), \tag{1}$$

A probabilistic framework is employed to build an estimate $\hat{f}$, of the non-linear state transition map f, based on the set of demonstrations. *Gaussian Mixture Models (GMM)* are used to directly embed the multi-variate dynamics of a motion through the encoding of the demonstrated data.

The *GMM* define a joint probability distribution $p(\xi^i, \dot{\xi}^i)$ of the training set of demonstrated trajectories as a mixture of the $\mathbf{K}$ Gaussian multivariate distributions $\mathcal{N}^k$, with π^k, μ^k, and Σ^k, respectively the prior, mean and covariance matrix, parameters of the Gaussian component k. The joint probability distribution, $p(\xi, \dot{\xi})$, for the *GMM* is given by,

$$\begin{gathered} p(\xi, \dot{\xi}; \theta) = \frac{1}{K} \sum_{k=1}^{\mathbf{K}} \pi^k \mathcal{N}^k(\xi, \dot{\xi}; \mu^k, \Sigma^k) \\ \text{with} \quad \mu^k = \{\mu^k_\xi; \mu^k_{\dot{\xi}}\} \quad \text{and} \quad \Sigma^k = \begin{bmatrix} \Sigma^k_\xi & \Sigma^k_{\xi\dot{\xi}} \\ \Sigma^k_{\dot{\xi}\xi} & \Sigma^k_{\dot{\xi}} \end{bmatrix} \end{gathered} \tag{2}$$

The mixture of Gaussian functions would estimate the non-linear function f, thus the unknown parameters of f, θ, becomes the prior, π^k, the mean, μ^k, and the covariance matrix, Σ^k, of the $\mathbf{K}$ Gaussian functions, such that $\theta^k = (\pi^k, \mu^k, \Sigma^k)$, defined as in Eq. 2.

To generate a new trajectory from the *GMM*, one then can sample from the probability distribution function $p(\xi, \dot{\xi})$, this process is called *Gaussian Mixture Regression (GMR)*.

4. REPRESENTING THE SKILL KNOWLEDGE

An important challenge for robots acting on unstructured dynamic environments, as is a requirement for humanoid robots, is in dealing with internal representation and understanding of the world. A key decision must be made on which aspects of the world to focus on and which aspects of the world to ignore, and how the knowledge about the world would be structured. Despite claims against the use of internal representation altogether, the abstractions are necessary because no system can possible manage a world model that includes the whole of the world. However, the representations must be limited and physically grounded to the environment, good representations must be selective and oriented to a particular use by a particular agent (Anderson [2003]).

A majority of approaches in cognitive architectures focus on skill knowledge about how to generate or execute sequences of actions, while often relegating equally important conceptual knowledge dealing with categories of objects, situations or other concepts (Langley et al. [2009]). Therefore, much of an agent's knowledge must consist of objects, concepts, actions, skills, situations, events.

The central task of a knowledge representation is capturing the complexity of the real world. Representations thus perform as functional abstractions of the perceived environment, encoding an agents knowledge about its world, objects, actions, events, etc., into manageable internal structures.

4.1 Representing Objects Knowledge

Organizing objects is a vital part of knowledge representation. For this it is needed to state out an ontology. It is essential to circumscribe the basic types of objects our knowledge base would have, and to determine the set of attributes that our objects can have. The ontology provides a set of features that serve to identify objects that can fit typical categories.

A typical problem building a representational approach is that knowledge about an object could be scattered around the knowledge base. The organization of the knowledge of objects in the world towards a manageable structure of objects knowledge is a critical aspect of the design of a knowledge base. Categories are the primary building blocks of knowledge representation schemes, the real world can be seen as primitives objects and composite objects build from them.

A system dealing with objects in the real world must deal with various different forms and types of knowledge. Minsky [1975], suggested the idea of using object-oriented groups of procedures, which where called frames. The frame concept offers a representation of an object or category, with attributes and relations to other objects or categories, assembling facts about particular object and event types and arranging the types into a large taxonomic hierarchy analogous to a biological taxonomy (Russell and Norvig [2010]). Frames focus mainly on the recognition and description of objects and classes. Minsky [1975] pictured a great collection of frames systems stored in permanent, when the perception evidence suggest one will fit a frame is evoked to working memory.

The frame knowledge structure can be seem as an instance of an object-oriented representation analogous to the development in a object-oriented programming language. This could allow the frame representation of objects to share many advantages of object-oriented programming systems, like the specification of general classes, logical control, inheritance of methods, encapsulation of abstract procedures, etc.

Table 1. Object Frames.

Object Frame: Example of generic object frame and instances of an object frame	
⟨Object-frame⟩ gObj	
⟨Color⟩ none ⟨/Color⟩	
⟨Volume⟩ 0 ⟨/Volume⟩	
⟨Roles⟩ obstacle ⟨/Roles⟩	
⟨Position⟩ 0 0 0 ⟨/Position⟩	
⟨Object⟩ ObjA	⟨Object⟩ ObjB
⟨instanceOf⟩ gObj	⟨instanceOf⟩ gObj
⟨Color⟩ Blue ⟨/Color⟩	⟨Color⟩ # FFFF00 ⟨/Color⟩
⟨Volume⟩ none ⟨/Volume⟩	⟨Volume⟩ none ⟨/Volume⟩
⟨Roles⟩ tool ⟨/Roles⟩	⟨Roles⟩ obstacle ⟨/Roles⟩
⟨Position⟩	⟨Position⟩
120 34 56 ⟨/Position⟩	30 -45 78 ⟨/Position⟩

Figure 1 present different modes for the representation of an object location knowledge. In this work the data structure of frames is used to store the knowledge about the objects. Table 1 shows an example of the object frame. A generic object frame is described, and two instances derived from the generic frame are also present. Instances of object frames inherits from the properties and default values of the generic frame, but this does not forbid it to have properties, and update its values, on its own. Object frame could also be instances of two or more frames or be composed of other object frames. Important properties of the object frames are its name, position and role values for their identification, localization and relation with the rest of the knowledge base.

4.2 Representing Actions Knowledge

The interrelation between the objects and actions representations, is a fundamental concern when executing tasks upon the world. The robots actions would generally involve the presence of an object, or several objects, plus the possible interaction with human partners.

Representations, to be valid for embedded cognition, are to be limited, physically grounded to the environment and oriented towards the specific needs of the given agent (Anderson [2003]). The distinction must not be made between representational and non-representational solutions but among the action-neutral forms of internal representations and more action-oriented forms of representation, in which the behavioural response is embedded into the representation itself (Clark [2004]).

When thinking of actions representations the concept of affordances is essential, the representation of objects and actions are related in terms of their affordances. The affordances are proprieties of the objects and of what kinds of interactions they can support.

General approaches from artificial intelligence and logic base reasoning see the world in more of as discrete time experiences. However, real-world action is a continuous time phenomena. To acquire an internal representation of an affordance, and agent must carry out a complex encoding of the sensory stimulus; to reproduce the action an agent must decode the encoded representation into proper signals. The embodied approach of cognition calls for the representations to be encoded in the body and not in the head (Anderson [2003]). A dynamical system theory approach to cognition provides a way to overcome the separation between mind and the world largely prevalent

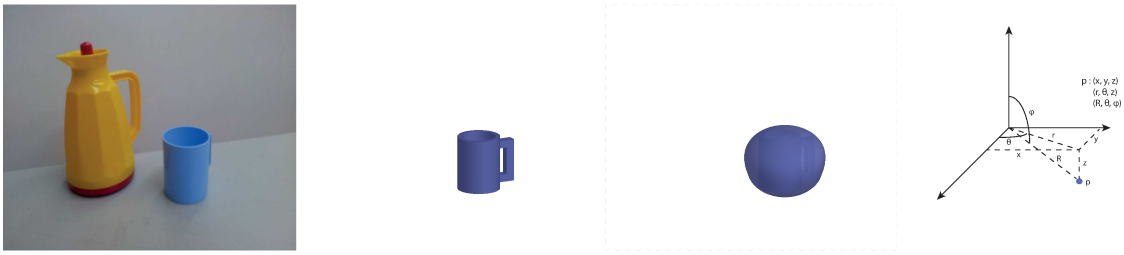

Fig. 1. Different modes for the representation of an object location knowledge. (left to right): The real-world object. 3D model representation of the object. Convex bounding volume representation of the object. Representation of the object in Cartesian, spherical or cylindrical coordinates.

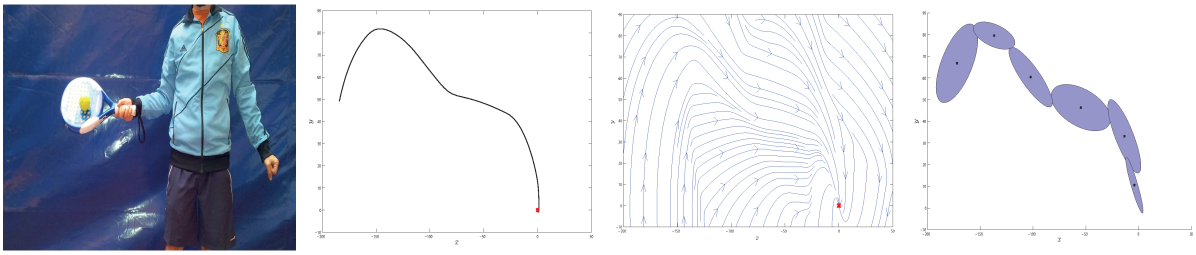

Fig. 2. Different representations for a skill action. (left to right): Real-world agent action execution. Trajectory representation of the action. Dynamic attractor landscape representation of the action. Encoding representation of the action dynamics in a Mixture Gaussian Model.

Table 2. Action-Affordance Frame.

Action Frame: Example of action-affordance frame	
⟨Action⟩ Act1	
⟨instanceOf⟩ gAct	⟨SkillModel⟩ $\mathcal{M}_{RS}1$
⟨iniConditions⟩ ... ⟨/iniConditions⟩	⟨Prior⟩ 0.302 .... ⟨/Prior⟩
⟨Skill⟩ $\mathcal{M}_{RS}1$ ⟨/Skill⟩	⟨Mean⟩ -424.72 .... ⟨/Mean⟩
⟨Object⟩ gObj2 ⟨/Object⟩	⟨Covar⟩4.04e+3 .... ⟨/Covar⟩

in most work in artificial intelligence (Bechtel [1998]). The dynamic systems theory provides an alternative to the traditional formats of representations, yet, despite their differences the approaches can be complementary (Bechtel [1998]). A wide variety of aspects of dynamical models can be regarded as having a representational status, such as states, attractors, trajectories, bifurcations, and parameter settings (van Gelder and Port [1995]).

Section 3 presented the framework for learning the robot skills. The robot skills ought to enclose the knowledge of the task to allow generalization of the skill for reproduction and to form full goal directed actions. The dynamical systems approach to skill learning can offer a fast, simple and powerful formulation for representing and generating movement plans. The robot skills are modelled by the parameters θ of $\hat{f}$. where $\theta^i = \{\pi, \mu, \Sigma\}$ of the $\mathcal{N}^i$ Gaussian function, defined by Eq. 2, are the prior, π^k, the mean, μ^k, and the covariance matrix, Σ^k, of the $\mathbf{K}$ Gaussian and they encode the representation of the skill action in a dynamical system.

Figure 2 shows different representations for a skill action. Table 2 shows an example of the action-affordances frame. Generic action frames have a linked model of the encoded skill action dynamics. In addition, to the model of the skill, the action frame links actions with the corresponding objects that afford them. Generic action frames list available objects for action, particular instances of an action frame presents only one object affordance for the execution of the action.

4.3 Representing Events Knowledge

Focusing on only on objects and actions would not be enough to develop the knowledge representation structures needed by the humanoid robotic systems. Representational attributes need to also take into account the state of the world, the current situation, grounding the representations to the environment, the task at hand and present events.

Minsky [1975], suggested the idea of using object-oriented groups of procedures to recognize and deal with new situations. A frame is a data-structure intended for representing a stereotyped situation. The idea behind the approach is that when one encounters a new situation one selects from memory a frame structure. When a proper frame is retrieved its slots are fill with available information, its default assignments become instantly available, and the more complex assignment negotiations are completed latter as they become available. The process of matching a proposed frame suitable to represent the current situation is controlled by the system current goals and by information attached to the frame. The representations of events is thus largely concentrated in two major frames. One of the system tasks and goals knowledge, and one representing the current state of the world knowledge.

Task event frames would hold knowledge for the requested execution of a task. Such as, the task goal, task actions, including proper instances of required action frames, task start, end and invoking conditions. Task events are instantiated from recognizing matching invoking conditions for the event frame or by directly giving the system high level commands. The representation of a world event frame would try to maintain an accurate model of the agent's en-

Table 3. Event Frame

Task Event Frame: Example of the task event frame
⟨Task-event⟩ gTask
⟨Goal⟩ ... ⟨/Goal⟩
⟨ActionSet⟩ act1 act2 ⟨/ActionSet⟩
⟨Status⟩ 0 ⟨/Status⟩
⟨Conditions⟩ ... ⟨/Conditions⟩

vironment, so the world frame holds knowledge of objects being perceived as well as the most recent assumptions of objects not longer in the current view that are reasonably thought to lie around.

In such a complex problem as working in dynamic environments it is not possible to cope with many details at once. At each moment one must work within a reasonably simpler framework.Humans do not process the whole of a scene, one constantly discriminates information from a scene, categorizing, grouping and discarding chunks of information. An engage worker would generally focus all of its attention in to very small region of features. To determine what would be the agent's view, its focus of executing attention, we propose to start from the two event frames, representing the task and world knowledge, and build from them a single frame of what constitutes the relevant aspects of the current view of the world, focusing on the knowledge for task execution. This event frame, called here execution view event frame, consist of knowledge from objects and relationships in the environment taken from the world event frame according to what the task event frame requires.

Table 3 shows a simplified example of the task event frame.

5. ROBOT SKILLS KNOWLEDGE BASE STRUCTURE

Our earlier attempts Hernández et al. [2009], at building a knowledge database of robot skills consisted on the pairing of pairing of objects and actions. Elements in the knowledge database were represented in two principal directions of objects and skill actions.

However, objects and actions alone does not provide sufficient and complete information for a robot situated in its environment to be able of performing its task adequately. For instance, for a single behaviour there could be more than one available pairing of ⟨ *object, skill model* ⟩, leading to ambiguities. To resolve this problems it is suggested to considered two more representational directives, one for the task goal, and one for the configuration of the current state of the world, mainly objects position and relations with themselves, the robot and a human operator. Figure 3 presents the organization of the knowledge base in terms of the frames describe in Section 4. The knowledge of the environment is represented in terms of World Event Frame and Task Event Frames, with Object and Action Frames representing knowledge about available objects and actions respectively. From the knowledge of this frames a Execution View Event Frame is built of the focused knowledge promoting the agent's execution.

The knowledge base needs to hold all necessary information for reproduction of the skills. Knowledge of the task would be distributed among the representation of objects, actions and events of the goal and the state of the world. A behaviour could be represented by the phrase ***"Do Action (A), To an Object (O), For achieving Goal (G), When State of the World is (W)"***. Therefore, the tuple formed by ⟨ *Do = Action(A), To = Object(O), For = Goal(G), When = World State(W)*⟩ holds all necessary information for the reproduction of the task behaviour. The robot extract from the received perceptual input the knowledge about objects, goals, and current state of its working environment. The robotic system would be able to retrieve an appropriate skill action from the knowledge base by finding the answer to the phrase ***"Do Action (?) ... "*** for its current task constraints when being presented with the triple ⟨*Object, Goal, World State*⟩.

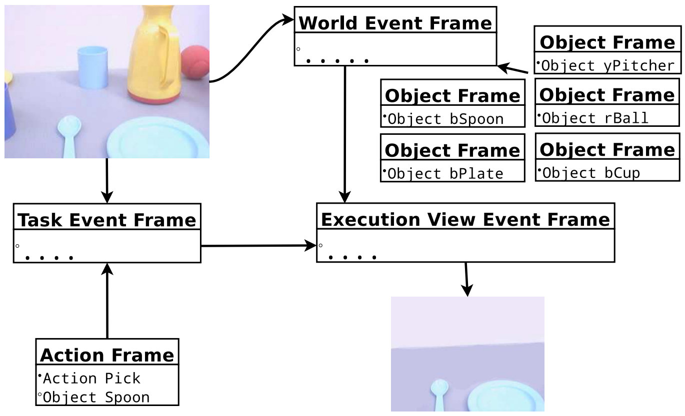

Fig. 3. Knowledge base structure and organization of the knowledge representations.

6. DISCUSSION

In this work we presented the development of a knowledge base for the storing and retrieval of the learned models of the skills. Section 2, reviewed some approaches aimed at building repertoires of basic robot motor skills which can represent a basic set of elementary movement primitives. The embodied view of cognition and its challenges to the traditional approaches of symbolic representations call for representations to be limited, physically grounded to the environment and oriented towards a particular use.

In sections 4.1, 4.2 and 4.3 approaches and problems for building representation of objects, actions, and events knowledge were presented. And section 5, presented the representational structure of the robot skills knowledge base developed in this paper.

Thinking in terms of objects and actions is not only intuitive but also convenient for a representational undertaking in robotics. Object and actions are at the basis of robot performance. However, representational attributions must include also information about the world and situations, events and goals, for effective situated performance.

The principal aim for the humanoid robot is to take actions, as situated agents, that are appropriate to its circumstances. Fitting representations are essential for this goal. Approaches from artificial intelligence and logic base reasoning see the world in more of as discrete time expe-

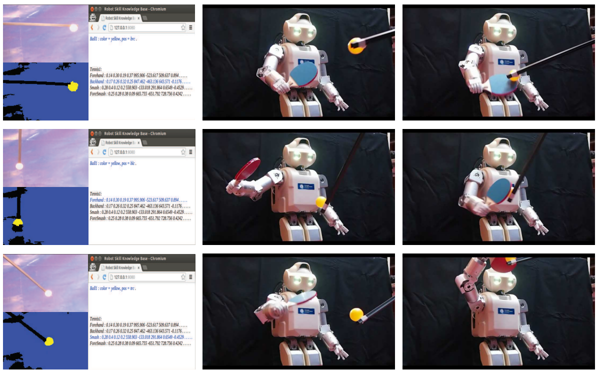

Fig. 4. Snapshots from the execution of the task, depending on the state of the environment and the knowledge base information the robot perform different skills.

riences. Yet the state and action representations are dynamic. The robot actions and thinking must be a process of interacting change in the environment. The dynamical system theory approach is an appropriate alternative to the traditional formats of representations. Dynamical systems can store knowledge and have this stored knowledge influence their behaviour (van Gelder and Port [1995]). The dynamical systems framework allows to comply with the attractor dynamics of a skill, modulating it with a set of non-linear dynamical systems that form an autonomous control policy for motor control.

Evaluation of robotic systems, and knowledge base robotics systems in particular, is a complicated issue in which there are not readily available standardized evaluations or established benchmarks Tenorth and Beetz [2013]. To validate the proposed systems a experiment was conducted with the humanoid robot. The demonstration will test the operation of the robot and the developed approach as it is required to complete distinct skills. For the experiment the *HOAP-3* humanoid robot is equipped with a table tennis paddle, and set of learned robot skills to perform different tennis shots. The purpose of this scenario is to prove the viability of the representations and knowledge base system for selecting the appropriate robot skills from its available action frames and perceived world state knowledge. Figure 4 presents snapshots from the execution of the task.

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