CHAPTER 21

NEW TRENDS AND CHALLENGES IN THE AUTOMATIC GENERATION OF NEW TASKS FOR HUMANOID ROBOTS

R. FERNANDEZ-FERNANDEZ, J. G. VICTORES and C. BALAGUER

RoboticsLab, Universidad Carlos III de Madrid, rauferna@ing.uc3m.es

In this paper, the study and implementation of a task generation system that uses the information obtained from the user and already known cases is presented. One of the main objectives of the system is to introduce a new approach in robotics that takes into account the physical limitation of teaching and learning time, and thus the amount of knowledge that a robot can obtain of a given environment (tasks, objects, user preferences…), as a critical bottleneck of any robotic system. For this, the study of the Case Based Reasoning (CBR) problem is presented. Additionally, Base Trajectory Combination (BATC), a novel trajectory combination method based on a simplified CBR structure, using trajectories instead of high-level tasks, is proposed and explained. Finally, this system is tested with Move-it! as the simulation environment, using the humanoid robot TEO from Universidad Carlos III de Madrid as the robotic platform. The results of these experiments are also presented with the corresponding conclusions and future research lines.

1 Introduction

The goal of this work is the design of a system capable of the automatic generation of new tasks, using both the information stored from old cases and from user interaction. This idea started since the first studies in human memory (Ebbinghaus, 1885), when the scientific community started to see how the knowledge stored in memory was used as a support for the generation of new tasks and even as a tool for predicting the future (Ingvar 1985), (Schacter, Addis, and Buckner 2007).

On the other hand, roboticists have yet to find a solution for most of the challenges that imply working in a real environment. However, in current systems, there is a tendency to use the knowledge of a robot as an infinite resource that contains all the knowledge already adapted to all the different circumstances that can occur. This leads us to highly knowledge dependent systems, which can only correctly within the specific domain for which they were designed. Therefore, one of the purposes of this work is to design a system able to work with a limited knowledge database. This means, a database with scarce knowledge that sometimes is not even related to the context where the system needs to work. This scenario is pretty similar to the case of the children during their first steps of learning, where their knowledge is quite limited. In turn, they use help of a constant interaction, habitually with their parents, for learning and executing new tasks (Wells, 2009). This is the reason why our objective will be to study and propose a system able to generate new tasks using the information retrieved from a limited knowledge database and user interaction.

2 State of the art

One of the base problems to solve is the CBR problem. This means, the idea of using previous cases to help with the achievement of new tasks. This idea started with the publication of (Schank and Abelson 1975), and in a relatively small time, some systems based on this idea started to appear. An example of this is CHEF (Hammond, 1986), which uses recipes as cases, or ISAC (Bonzano, Cunningham, and Meckiff 1996), a system to support air-traffic controllers. The basic overall structure used in CBR systems was presented in (Kolodner 1992), and can be seen in Fig. 1.

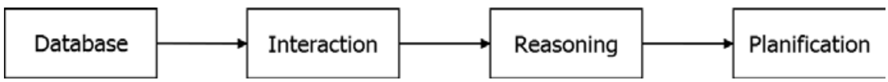

Fig. 1. Overall scheme of all the process involved in a CBR system.

Since the proposal of this structure, some papers have appeared with the objective to solve some specific CBR problematics presented in this structure. This is the case of PARADYME (Kolodner, 2014), a case retrieval method for the retrieval of old cases. However, the number of this kind of publications is quite low in comparison with the ones oriented to applications. The reason is because the problems presented in CBR systems are complex high level problems of which most are not yet solved. This is especially notable in the reasoning stage. This stage concerns solving problems like the adaptation of high level tasks and the evaluation of the tasks generated, problems that presents a huge challenge for the implementation of a CBR system.

In addition to this, there are some similar projects that face similar problems to the ones presented in this paper. In (Beetz, 2011) a system designed to generate new tasks using the information from pages like *wikihow.com* or *ehow.com,* and the information stored in a KnowRob[1] ontology database is presented. Another example is (Ramirez-Amaro, 2015), in this case the system is focused in the design of semantic rules that allow the conceptual definition of tasks from user demonstration. The goal is to later use this conceptual definition to allow the robot to perform the task under different circumstances, and to make the process of learning a new task easier at the same time, using for this the information from known cases for the generation of the new ones. In (Morante, 2014) the idea was to design a task generalization method based on the idea of using the information about the changes that an action produces in the environment. This means instead of working with tasks defined as robot movements, to work with tasks defined as changes in the environment.

3 BATC

The idea of BATC[2] is to use the trajectories that define the tasks, before attempting to directly use the tasks themselves. The goal of this is triple. First, since BATC uses trajectories, it can be later used for the implementation of a high level CBR system. Second, since BATC uses low level cases, most of the problems presented in a CBR system become easier to solve. Finally, the last reason is because the implementation of BATC would be solving a not solved problem in robotics, which is the combination of known trajectories for the generation of new ones.

3.1 The idea behind BATC

The idea behind BATC consists in using a mathematical method, since trajectories are mathematical functions, for the combination of these trajec-

1 http://www.knowrob.org/

2 https://github.com/roboticslab-uc3m/teo_batc

tories, in this case a weighted sum. This way, in BATC a feature vector is assigned to every trajectory in order to compare them (Fig. 2).

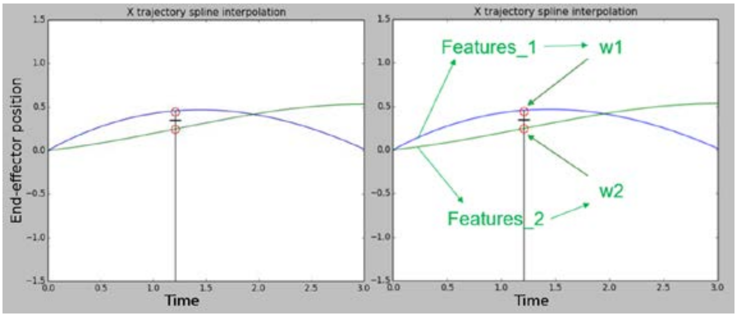

Fig. 2. In BATC the new point is defined using the points in the database (left), and a weighted sum with the weights assigned using features vectors (right).

3.2 The BATC algorithm

Using the feature vector and the Euclidean distance, the two best trajectories (the ones closer to the goal trajectory) are selected. Then, the base one weights are assigned using the Euclidean distance between the base trajectories and the goal one. The new trajectory will be then the spline defined by the succession of points presented in the equation 1, where *Sp1(t)* and *Sp2(t)* are the values of the trajectories splines at the instant t, w_1 and w_2 are their respective weights, and the difference between t and $t+1$ is the time step used to define the new trajectory. This way, changing the weights, we can adapt the trajectory generated to the needs of the user.

$$Tr = [Sp_1(t) * w_1 + Sp_2(t) * w_2, Sp_1(t+1) * w_1 + Sp_2(t+1) * w_2 ...] \quad (1)$$

In the case of orientation, since BATC works with quaternions (nonlinear units), the SLERP method for the interpolation of quaternions is used instead of the weighted sum. The new orientation can be defined as the succession of quaternions obtained using equation 2. Where, $q_1(t)$ and $q_2(t)$ are the two quaternions of the base trajectories in the instant t. The value w_1 is the weight of $q_1(t)$, obtained the same way as in the case of SPLINES.

$$NewOri = SLERP(q_1(t), q_2(t), w_1) \quad (2)$$

The CBR structure in Fig. 1 was used as the base structure for the implementation of BATC: First, the trajectories are stored in a database with its features vector. Next, there is an interaction step where the user specify the features of the goal trajectory. Then, the BATC reasoning system generates the new trajectory, using the trajectories in the database and the information from the user. Finally, the new trajectory can be executed.

4 Experiments

For the implementation of the BATC system, Moveit![3] and ROS were used as the simulation software, with TEO the humanoid robot (Martinez, 2012) from the Universidad Carlos III de Madrid, as the robotic platform. Results obtained are shown in Fig. 3. Here, two base trajectories stored in the robot database ("arm to the front" and "arm up") were used for the generation of the new one, defined with its final position.

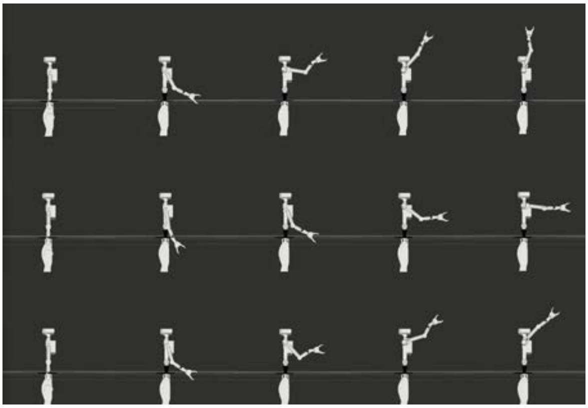

Fig. 3. The first row corresponds to the "arm up" trajectory, the second one is "arm to the front", and the last one is the generated one "arm to the diagonal".

The experiment performed to test BATC consisted in changing the number of trajectories in the database, and studying how the system behaves with a set of random goals. The results of these tests can be seen in Table 1. The error obtained is the sum of the final position error, bounded in *[0.0 , 1.5]* in Moveit! units, plus the orientation error *[0.0 , 0.1]*. The first conclusion we can extract, is that adding just one more trajectory "arm to the back" the mean error, is now decreased by almost the half. One of the reasons of this is because the new trajectory is the opposite of "arm to the front" in the "x axis". This implies that we are maximizing this defined space, and therefore the performance obtained by BATC. On the other hand, in the third scenario the new trajectory is "arm to the x diagonal", a

3 http://moveit.ros.org/

variation of "arm to the front". The results this time, are quite similar to the ones obtained in the last experiment. This leads us to the conclusion that the more different are the base trajectories, the more information the BATC system has, and the better the performance.

Table 1. Experimental results with BATC.

Experiment Number	Configuration error 2 base trajectories	Configuration error 3 base trajectories	Configuration error 4 base trajectories
1	0.746	0.279	0.256
2	0.315	0.432	0.774
3	0.508	0.565	0.464
4	0.732	0.489	0.616
5	0.328	0.253	0.172
6	0.473	0.372	0.686
7	0.687	0.263	0.236
8	0.676	0.303	0.521
9	0.194	0.174	0.095
10	0.668	0.447	0.366
Mean error	0.492	0.337	0.351

5 Conclusions and future ideas

The overall idea of this work was to present a new approach in the area of robotics, using the knowledge as another limitation of the system. To do this, the study of the resolution of the CBR problem in a limited knowledge scenario was presented. Several contributions have been made:

- The presentation of the Base Trajectory Combination (BATC) system, a novel method for the automatic generation of new trajectories using the information from already known trajectories and user interaction. This method is designed to be able to work in scenarios where the robot's knowledge (set of trajectories in robot memory) is scarce.
- The integration of BATC and TEO in the ROS environment has been presented, using Moveit! as the trajectory planning software. This integration opens the possibility of future works that can make use of this state of the art software and TEO.
- The BATC implementation and behavior has been tested, using different experiments and scenarios, with the main goal to study how this system behaves when having to cope these different situations.

Furthermore, the ideas presented in this paper and the implementation of BATC have given us some ideas about future trends in the area of robotics:

- The design of new systems that are able to work using a generic database with limited knowledge.
- The generation of robotic systems that are able to learn new concepts and tasks using the interaction with the environment, the user, and the information stored from already known cases.
- New approaches that take into account the physical limitation of teaching and learning time, and thus the amount of knowledge that a robot can obtain of a given environment, as a crucial bottleneck of any robotic system.

Acknowledgements

This research has received funding from the RoboCity2030-III-CM project (Robótica aplicada a la mejora de la calidad de vida de los ciudadanos. Fase III; S2013/MIT-2748), funded by Programas de Actividades I+D en la Comunidad de Madrid and cofunded by Structural Funds of the EU.

References

Beetz, M., U. Klank, I. Kresse, A. Maldonado, L. Mosenlechner, D. Pangercic, T. Ruhr, and M. Tenorth. 2011. 'Robotic Roommates Making Pancakes'. In 2011 11th IEEE-RAS International Conference on Humanoid Robots (Humanoids), 529–36.

Bonzano, Andrea, Pádraig Cunningham, and Colin Meckiff. 1996. 'ISAC: A CBR System for Decision Support in Air Traffic Control'. In Advances in Case-Based Reasoning, edited by Ian Smith and Boi Faltings, 44–57. Lecture Notes in Computer Science 1168. Springer Berlin Heidelberg.

Hermann Ebbinghaus. 1885. 'Memory: A Contribution to Experimental Psychology'.

Ingvar, D. H. 1985. '"Memory of the Future": An Essay on the Temporal Organization of Conscious Awareness'. Human Neurobiology 4 (3): 127–36.

K. J. Hammond. 1986. 'CHEF: A Model of Case-Based Planning'. In Proceedings of the Fifth National Conference on Artificial Intelligence (AAAI-86).

Kolodner, Janet L. 1992. 'An Introduction to Case-Based Reasoning'. Artificial Intelligence Review 6 (1): 3–34.

Kolodner, Janet L. 2014. 'Selecting the Best Case for a Case-Based Reasoner'. In 11th Annual Conference Cognitive Science Society Pod. Psychology Press.

Morante, S., J.G. Victores, A. Jardon, and C. Balaguer. 2014. 'Action Effect Generalization, Recognition and Execution through Continuous Goal-Directed Actions'. In 2014 IEEE International Conference on Robotics and Automation (ICRA), 1822–27.

Ramirez-Amaro, Karinne, Michael Beetz, and Gordon Cheng. 2015. 'Transferring Skills to Humanoid Robots by Extracting Semantic Representations from Observations of Human Activities'. Artificial Intelligence, August.

Schacter, Daniel L., Donna Rose Addis, and Randy L. Buckner. 2007. 'Remembering the Past to Imagine the Future: The Prospective Brain'. Nature Reviews Neuroscience 8 (9): 657–61.

Schank, Roger C., and Robert P. Abelson. 1975. 'Scripts, Plans, and Knowledge'. In Proceedings of the 4th International Joint Conference on Artificial Intelligence - Volume 1, 151–57. IJCAI'75. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

S Martinez, CA Monje. 2012. "TEO: Full-Size Humanoid Robot Design Powered by a Fuel Cell System." Cybernetics and Systems 43 (3): 163–80.

Wells, C. Gordon. 2009. The Meaning Makers: Learning to Talk and Talking to Learn. 2nd ed. New Perspectives on Language and Education. Bristol, UK; Buffalo, NY: Multilingual Matters.