Neurocomputing 77 (2012) 71–81

Contents lists available at SciVerse ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Hierarchical behavior categorization using correlation based adaptive resonance theory

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ARTICLE INFO

Article history:
Received 8 February 2011
Received in revised form
11 June 2011
Accepted 17 August 2011
Communicated by R. Tadeusiewicz
Available online 29 September 2011

Keywords:
Robot behavior categorization
Machine learning
Adaptive resonance theory

ABSTRACT

This paper introduces a new model for robot behavior categorization. Correlation based adaptive resonance theory (CobART) networks are integrated hierarchically in order to develop an adequate categorization, and to elicit various behaviors performed by the robot. The proposed model is developed by adding a second layer CobART network which receives first layer CobART network categories as an input, and back-propagates the matching information to the first layer networks. The first layer CobART networks categorize self-behavior data of a robot or an object in the environment while the second layer CobART network categorizes the robot's behavior with respect to its effect on the object. Experiments show that the proposed model generates reasonable categorization of behaviors being tested. Moreover, it can learn different forms of the behaviors, and it can detect the relations between them. In essence, the model has an expandable architecture and it contains reusable parts. The first layer CobART networks can be integrated with other CobART networks for another categorization task. Hence, the model presents a way to reveal all behaviors performed by the robot at the same time.

1. Introduction

There is no common definition for behavior. Nevertheless, it is generally defined as a reaction to a stimulus. This study considers behavior as a time-extended action that achieves a set of goals [1], and causes changes in the environment or to the robot itself. The aim of this study is to categorize behaviors in order to elicit alternative forms of primitive behaviors and to find relations between them. This process can help the construction of a base for behavior learning and generation, and it may be used for behavior recognition of objects moving around.

The idea of developing a base model for behavior recognition and learning tasks encouraged us to focus on the behavior categorization. Thereby, behavior categorization by ART 2 (adaptive resonance theory) network was implemented by Yavaş and Alpaslan [2]. ART 2 [3] introduces a method of self-organization and stable category recognition via unsupervised competitive neural networks, which is used to categorize arbitrary sequences of continuous-valued input patterns. The experiments showed that behaviors are not stabilized even after long-time learning, and some similar behaviors are matched with different categories, and unrelated data are grouped within the same categories. These deficiencies arise from the fact that continuous update of categories looses all or some information concerning old categories.

A priori SOM (self-organizing map) categorization was combined with ART 2 categorization, having the idea that topological representation of the behavior data by SOM can result in better categorization by ART 2. SOM is a competitive learning method based on feature mapping [2]. The main idea behind the SOM method is arranging the location of output units on the plane in a way that it reflects the input topology in the best way [4,5]. The experiments over SOM and ART 2 by Yavas and Alpaslan [2] showed that using a priori SOM categorization did not increase the behavior categorization performance of ART 2. After having these results, CobART categorization was applied to behavior data. The experiments showed that the performance of CobART is more reasonable than ART 2, even when behavior data was fed into a SOM network prior to its topological mapping output was categorized by ART 2 [2]. However, it can be observed from the experiments that CobART itself is not enough for behavior categorization. The CobART discriminates different behaviors but it may generate more than one category for similar behaviors. Generation of multiple categories for the similar behaviors does not mean inadequacy, because it is also a need to learn different forms of the behaviors. Nevertheless, the relation between these categories shall be revealed for correct behavior recognition and learning tasks. Therefore, it was concluded that there is a need for a method that can differentiate fast and slow motion of the robot, and can understand that both of them are types of the similar behavior.

This study uses CobART, which is a new type of unsupervised, self-organizing stable category generation network that performs satisfactory categorization for the domain where patterns are

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doi:10.1016/j.neucom.2011.08.022

constructed from consecutive continuous-valued inputs [2]. CobART is a type of ART 2 network, where correlation analysis methods are used for category matching. It has more modular and simpler architecture, and it can be easily adapted to different domains. This study is motivated from the behavior categorization using CobART research, and is developed to enhance categorization results. Although the experiments show that the performance of CobART is reasonable, the model should be improved in order to be used for behavior recognition and learning. Hence, hierarchically integrated CobART network is developed by adding a second layer CobART network that applies extra categorization over the first layer networks' category outputs. Thus, robot motion, object motion and distance data are categorized with different CobART networks at the first layer, and category outputs of these networks are fed into the second layer CobART network as an input resulting in second categorization process. Besides, correlation scores between the categories, and category matching information from the second layer are used to calculate the category similarity. The experiments over the hierarchical model show that new model outperforms the single categorization by CobART.

The proposed model was tested by *Khepera* robot using *Webots* simulator. *Pushing*, *approaching*, and *striking* behaviors are selected for testing purpose. The simulator was programmed for each behavior to collect Khepera's own sensory inputs as a training and test data. Multiple runs were performed and the motion data was logged for each run. The robot was made to move from various distances with varying velocities in order to collect various data.

The remainder of this paper is organized as follows. First, we introduce related work in Section 2. Background information about ART 2 and our CobART model is presented in Section 3, and the proposed hierarchical model is explained in Section 4. We explain the experimental evaluation of the alternative behavior categorization models in Section 5. We report the concluding remarks in Section 6.

2. Related work

The studies on behavior recognition and learning are far from satisfactory levels. Following papers may give a rough idea about the way these studies are carried out. Fox et al. [6] present a machine learning approach that elicits internal steps of the navigation behavior from raw sensor data using Kohonen networks and hidden Markov model. Infantes et al. [7] proposed a generic model for learning the behavior model of the robot for a given task, using observation data. The model is developed by using dynamic Bayesian network and dynamic decision network, and is tested with navigation task. Tani [8] presents a novel hierarchical neural network for behavior learning. A model which includes a two layer recurrent neural network (RNN) running on different time scales learns the sequence of the defined primitive behaviors. The lower level RNN learns primitive behaviors and the top level RNN learns the sequences between the primitive behaviors and time spent on each one of them. In addition, Paine and Tani [9] proposed a model based on two-layer recurrent neural network and genetic algorithm. The model is tested with a navigation task. Genetic algorithm is used to learn some network parameters. Fung and Liu [10] worked on robot behavior learning that uses a specific neural network named as behavior learning/operating modular (BLOM) architecture which is formed by the integration of the ART networks and associative memories. Sensory inputs are categorized into S-categories and action outputs are categorized into A-categories using fuzzy ART networks. Associative memories are used for establishing association between the S-categories and A-categories. Vigilance parameter is not used as a constant value but is changed according to game-theoretic approach. Han and Veloso [11] present high-level robotic behavior recognition from low-level sensor inputs using augmented hidden Markov model. The states of the model are defined as a priori information. Robotic soccer game is selected to use the proposed approach in order to recognize opponent's behavior and to narrate the game. Gu and Su [12] worked on categorization of joint actions using ART 2 networks. A separate ART 2 network is dedicated for each joint action. Generated categories are interconnected with behavior labels uttered by the instructor. Morisset and Ghallab [13] introduce a model that learns performing appropriate skills for current state to accomplish a given task. The model contains a number of built in sensory-motor functions. A set of skills using these functions are defined by hierarchical task networks. The model learns which skill to apply by using Markov decision processes. Peula et al. [14] present a supervised reactive behavior learning model. In the training phase, a human supervisor controls a test robot to perform target tasks while the robot collects sensory data and corresponding motion commands to learn their association using case based reasoning technique. Yang and Li [15] worked on a model that is designed using subsumption architecture. Fuzzy logic control is applied to the obstacle avoidance behavior. The proposed model uses genetic algorithm for vision based landmark recognition.

Kubota [16] presents interactive learning between instructor and a robot based on imitation. In this study, spiking neural networks are used for extracting spatial and temporal information of human gesture patterns and self-organizing maps are used for gesture classification, while a steady-state genetic algorithm is used for action pattern generation with respect to human gestures. Another interactive imitation learning which is proposed by Ito and Tani [17] presents a novel imitative model that can learn several movement patterns. The model is developed by using recurrent neural network with parametric bias (RNNPB). Borenstein and Ruppin [18] present a specific framework for imitation learning. The proposed approach consists of a specific neural network and evolution using genetic algorithms. Environment data and demonstrator's actions are inputs to the neural network while motor commands are the outputs. Genetic algorithm is applied on the network parameters. The fitness of the individuals are calculated based on the properness of the actions that they performed. Billing and Hellstrom [19] worked on behavior recognition using learning from demonstration (LFD) techniques. They introduce β-Comparison, AANN-Comparison (autoassociative neural networks comparison) and S-Comparison techniques for this purpose and compares their performance. Kelley et al. [20] present a method for intent recognition of the agents from robot's perspective. To do that, hidden Markov models are constructed for each behavior, and these models are trained by applying the behaviors with the robot. After learning is completed, the robot can be used as an observer to calculate necessary parameters from the agent's perspective in order to recognize agent's intent as early as the activity is started. Palm and Iliev [21] worked on grasp recognition task and compared the performance of the following three methods; a method using distance between time clusters, qualitative fuzzy recognition rules, and time cluster models with HMM. Palm et al. [22] present a way of modeling and recognizing robot skills. In order to do that, robot captures the motion data first, while the demonstrator performs the target skills. The training of the system is performed by segmentation of skills into the phases and phase modeling by using fuzzy time clustering technique. Inamura et al. [23] worked on mimesis that is one of the framework models in cognitive psychology which explains how human learns behavior by