A learning and memory architecture for robot companions based on incremental associative learning

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Abstract—We present a learning and memory architecture that allows a robot companion to incrementally learn and associate data from different sensors and actuators. We use a topology learning algorithm that clusters the received inputs into discrete categories. On top of these clusters we apply associative learning methods to store co-occurrence relationships in an associative network. We evaluated the incremental clustering capabilities on two datasets and further performed a real experiment on associative learning where a robot learned by demonstration to associate visual perceptions with motor readings. We give a short overview of the obtained evaluation results and the experiment outcomes and we also highlight advantages of the presented architecture.

I. MOTIVATION

A robot companion must be able to cope with various environments and adapt its behaviour depending on the current circumstances and requirements [1]. In order to do so, the robot must learn about its surroundings using only data that is available via its sensors. Ideally, a robot companion should not be limited to a specific domain and must be able to incorporate new information at any time. Equipping artificial companions with such learning and memory capabilities is the overall challenge of the work presented here [2].

We propose a learning and memory architecture with the following goals in mind: the system must be able to deal with any kind of sensory data (1), learn incrementally (2) and work unsupervised (3). First, sensory data can usually be expressed as multi-dimensional real-valued vectors. However, neither the type of sensor nor the nature of the data is given in advance. Hence, the employed algorithms must be generally applicable which permits the usage of any informed preprocessing. Second, as the entire data to be learned cannot be known in advance and novel inputs can arrive at any time, learning should happen incrementally. The system must incorporate new data without overwriting existing knowledge. Third, we favour an unsupervised learning method. We can neither expect that labelled data is always available nor does the system receive any form of feedback on whether the learning process will generate successful outcomes in the future.

II. PROPOSED ARCHITECTURE

Our approach, the Incremental Clustering & Associative Learning Architecture (ICALA), consists of two main processing parts, the Modified Self-Organizing Neural Network (M-SOINN) and the Temporal-Order Sensitive Associative Memory (TOSAM). The M-SOINN can be used modularly to simultaneously exchange data with different modalities. The TOSAM can process data from multiple such modules. Therefore the architecture is applicable to different sensor/actuator configurations of various robots.

The M-SOINN is an incremental clustering method which transforms incoming sensory data into symbolic categories. The algorithm groups similar inputs together into different clusters and can then match later inputs with stored clusters. The method tolerates noise and abstracts from small variations in the incoming data stream. The M-SOINN is based on the Self-Organizing Incremental Neural Network [3] and inherits aspects from the Growing Neural Gas algorithm [4] as well as from the Enhanced Self-Organizing Incremental Neural Network [5]. We also added some further modifications which include joining clusters as well as removing edges and nodes in order to refine the topology.

The TOSAM is an associative learning method which forms and maintains relationships between these learned clusters. The formation of an association depends on the co-occurrence of the corresponding inputs [6]. The TOSAM consists of a fully connected network of units which store the perceived inputs. The connections between units are directed and their weights represent corresponding associative strengths. Learning is driven by the co-occurrence of different perceptions which strengthens the association between respective units. Each perception activates the corresponding unit in the network which, in turn, spreads activation to other units. For highly activated units, the stored information can be considered as recalled. By recalling associated information, the TOSAM can perform inference from one unit to another and pattern completion for patterns distributed over multiple units. Furthermore, the TOSAM can be used for prediction by simulating respective inputs for a desired situation.

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III. EVALUATIONS

With the M-SOINN we conducted evaluations on two different datasets. These were the MNIST database of handwritten digits\(^1\) as well as the AT&T database of faces\(^2\). In the case of the MNIST database, images of handwritten digits should be ideally grouped into 10 clusters, corresponding to the digits 0 to 9. Also for the AT&T database the resulting topology should contain 10 clusters as we chose the portrait images of 10 different people.

Such an optimal clustering was not achieved for any of the datasets. When running the algorithms without any of the introduced modifications, the topology contained less than 10 clusters which permits a proper representation of the data. This deficit was overcome when using the modifications. However, often the topology contained significantly more clusters than actually required. In this regard, some modifications made the algorithm more demanding in terms of storage space, but also set the foundations for better recognition as a higher amount of the presented data was memorised. A bigger topology is certainly more useful than completely missing out certain inputs. The latter case directly eliminates the chance to form associations with respective inputs. Overall, produce good topologies across all of the tested scenarios (which differed in the order of data presentation). But, in general, we found that the usage of the modifications for connecting new nodes and reducing the local error by node insertion generated good results.

We also tested the functionality of the whole architecture in a real scenario. Here a robot (NAO T14\(^3\)) had to learn to associate visual inputs from its camera with different poses of its arms. After training, the robot was presented each of the learned visual patterns and needed to position its arms into the associated arm pose. As visual patterns we used the images of different road signs; an arm pose was represented by the angles of shoulder and elbow joints. While learning, the robot’s arms were manually positioned and held by the experimenter which corresponds to the method of kinesthetic teaching [7]. The experiment setup is illustrated in Figure 1.

We measured the time it takes for the M-SOINN to form a single stable cluster for each of the distinct inputs. We observed short learning times below 1 minute (150 inputs at 2.5 Hz) for learning one arm pose (which is rather low-dimensional data). The high-dimensional image data of each road sign required much longer time to learn with durations of more than 10 minutes (3000 inputs at 5 Hz). This learning time could be shortened to ca. 5 minutes (1500 inputs) if the camera images were blurred before being processed by the M-SOINN. We then included the associative learning to relate a road sign to an arm pose and used each sign to recall the corresponding pose. The formation of associations did not take very long and we noticed that a shorter learning time of only 1 minute (300 visual inputs at 5 Hz) was sufficient to enable full recall. In this case, the different perceptions of a single road sign were not merged into one cluster yet but were still distributed over multiple clusters. Nevertheless, as associations to the corresponding arm pose were trained from each of these clusters, the robot could recall this pose independently of the exact perception of the sign. This confirms the assumption made earlier that a more than optimal number of clusters is still adequate for an associative learning task. While the system first distinguishes between smaller variations in the inputs of one category, over time more and more inputs lead to the formation of a single cluster. In this sense, more experience with certain stimuli helps to form a stable and complete representation of the corresponding category.

IV. CONCLUSIONS

We presented the ICALA consisting of the M-SOINN to perform incremental clustering and the TOSAM for associative learning.

The evaluations of the M-SOINN revealed that no single best modification configuration exists for all the tested scenarios. The clustering results achieved by the algorithm were suboptimal. Nevertheless, produced topologies are still sufficient for associative learning and recall, as was demonstrated with the robot experiment. For a short period of learning the TOSAM was able to form many-to-one associations and could correctly retrieve the respective response action for all given stimuli. The system tolerated the noise produced by the robot’s camera and could generalise over small variations in the perceived inputs.

Overall, the modular structure of the architecture makes it flexible enough to be used with various diversely equipped robots. The approach can be applied to any kind of (real-valued vector) inputs without requiring specific knowledge about the nature of the data. Also the capability of learning online adds to the system’s straight-forward applicability, especially when working with robot companions. In this regard, learning by demonstration offers a highly intuitive way for teaching or tutoring a robot.

REFERENCES