Towards Self-Awareness in Multi-Robot Systems

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I. INTRODUCTION

Self-awareness (SA) is a broad concept borrowed from cognitive science and psychology that describes the property of a system, which has knowledge of "itself," based on its own senses and internal models. This knowledge may take different forms, is based on perceptions of both internal and external phenomena, and is essential for being able to anticipate and adapt to unknown situations [2]. Deploying this concept on robots poses some fundamental challenges and requires some key capabilities of autonomous robots: (1) learn inference models from sensor inputs, (2) infer its state and the environment's state based on the models, and (3) detect abnormalities between observed and inferred behaviors. An abnormality detection may indicate a new phenomena observed by the robot and trigger the creation of a new model. Over time the robot acquires a set of models representing different phenomena.

This work proposes a framework towards self-awareness in multi-robot systems and presents preliminary results from a simulation study. In particular, we adopt hierarchical dynamic Bayesian networks (DBN) for modelling the observed internal (via proprioceptive sensors) and external (via exteroceptive sensors) phenomena [5]. Hierarchical DBNs allow to perform inferences and contextualize proprioceptive and exteroceptive sensory data at different abstraction levels. These inferences serve then as input for abnormality detection. We further extend modelling to multi-robot systems by coupling hierarchical DBNs.

II. FRAMEWORK

Even though current studies [4], [3] suggest detecting abnormality from an inference model trained by evenly ordered exteroceptive and proprioceptive sensory data, we suggest deriving independent inference models for each of these types of sensors and pair only exteroceptive models with a following proprioceptive model. As such, the robots can (1) choose the most appropriate proprioceptive inference model according to the best predicting exteroceptive model, (2) deduce preferred next states from proprioceptive most probable states derived from its inference model to be used for control decisions, and (3) ignore exteroceptive observations for which no control decision should be made internally.



Fig. 1. The proposed SA framework learns offline proprioceptive and exteroceptive models which are used for online abnormality detection.

Figure 1 depicts our proposed SA framework for a multirobot system. Proprioceptive and exteroceptive sensor data is preprocessed and either forwarded to offline learning or online abnormality detection. In the offline phase, two models based on coupled hierarchical DBNs are learned from the observed behavior of the robots. In the online phase, inferences from the learned models are compared with the current observations. An abnormality indicates a deviation between learned and observed behavior and may trigger the learning of new models.

A. Coupled hierarchical DBNs

Causal-temporal behaviors can be modeled by DBNs, which also support a hierarchical representation using various well-known approaches. For example, Kalman filters can be used for the continuous level, whereas particle filters can be used for the discrete level. We thus adopt DBNs for our modelling approach (cp. Figure 2). We cluster the observed sensor data Z into a sequence of quasi-stationary segments where the continuous state X represents the behavior within a segment and each segment corresponds to an abstracted state S. Coupled DBNs introduce an additional coupling layer D between multiple DBNs and causal relationships among the abstract state variables to model the interaction between multiple robots.

B. State transition and Abnormality Detection

For collective behavior, we couple the contributing individual behaviors based on their abstract states and refer to the possible combinations as coupled state D. State transitions indicate changes of quasi-stationary behaviors and are modelled by a matrix of state transition probabilities computed by the occurrence of successive coupled states according to closest observations.

Abnormality detection is founded on measuring the distance between the most probable coupled state prediction and the current observations of multiple robots. In particular, we

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Fig. 2. Hierarchical coupled DBN. Horizontal lines present temporal relationship between random variables at two consequent time steps t and t-1. Vertical lines present the causal relationship between them. Z represents the observation, X the continuous state, S the abstract level state, and D the coupled state. π represents the transition probabilities at different levels and λ the occurrence likelihood of states according to lower level parameters.

use the Kullback–Leibler divergence between the center of the forming abstract states of D and the robots' observation as abnormality value. If this value exceeds a threshold the current abstract state is inconsistent with the observed behavior triggering the creation and training of a new coupled DBN model.

III. PRELIMINARY RESULTS

We conducted a simulation study with the multi unmanned aerial vehicle (UAV) simulator CTU-MRS [1] which is built upon the Robot Operating System (ROS). We use four scenarios where two UAVs fly along rectangular trajectories and capture GPS position as proprioceptive data and LIDAR measurements as exteroceptive data for our study. These multi-UAV scenarios are implemented in a leader-follower architecture using model-predictive control for the Pixhawk 4 autopilots. One scenario serves as reference scenario¹ for learning the initial models (cp. Figure 3 left), whereas the others serve as test scenarios that include some blockage along the planned trajectories resulting in some evasive manoeuvres of the UAVs².

We trained the coupled DBNs with the captured GPS and LIDAR data from 10 simulation runs. The sensor data was clustered into 75 abstract states (cp. Figure 3 right). Figure 4 (top) shows the abnormality values for the reference and one test scenario. The abnormality values (Kullback–Leibler divergence) for the reference scenario remains below 10^3 units while for the test scenario, they reach approximately to 5.0×10^5 units in the regions where the blockage happens.

Figure 4 (bottom) shows the abnormality values for the LIDAR. For feature extraction of the LIDAR data, we used an artificial neural auto-encoder with 5 layers each for the encoder and the decoder and reduced the LIDAR scans to 2 dimensions. The abnormality value increases before the UAVs enter the blockage area. This early detection is



Fig. 3. Two UAV reference scenario (left) and clustering of the GPS data to form coupled states (right).

expected since the LIDAR can scan the environment of some distance.



Fig. 4. Abnormality values of the reference (blue) and test (red) scenario using the proprioceptive model and GPS data (top) and the exteroceptive model and the LIDAR data (bottom). The evasive UAV behavior in the test scenario results in a significant increase of the abnormality value.

IV. CONCLUSION

We introduced a framework towards self-awareness in multi-robot systems capable of learning offline proprioceptive and exteroceptive models which can be used for online abnormality detection. As future work we plan to expand our simulation study to more complex scenarios including different sensors, to investigate alternative distance metrics for abnormality detection, and to efficiently rank the validity of multiple models.

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