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.

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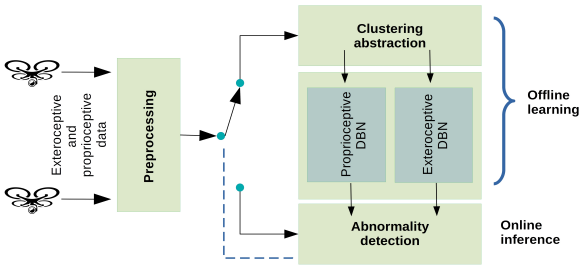

Fig. 1. The proposed SA framework learns offline proprioceptive and exteroceptive models which are used for online abnormality detection.

Figure 1 depicts our proposed SA framework for a multi-robot 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