Collective Self-awareness in Multi-Robot Systems

Mohammad Rahmani

DECIDE Doctoral School

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Self-awareness(SA) in Biological Intelligent Agents (IA)

A Biological IA is conscious/SA if

- It is born with an initial knowledge in the form of temporal cause-effect (Called experience from here)
- It has the ability to make a distinction between new experiences and old experiences.
  - The ability to make a distinction between known and unknown, if known can be built of different pieces of previous experiences (alphabet) otherwise it is unknown.
- Memorize new experiences.
- Invoke the right experience whenever it witnesses the evidence.
- This presentation only discusses detecting new experiences.

SA for single Artificial IAs

- Should implement the aforementioned characteristics in a SA.
- The very first step is to introduce a model to encode the experiences including the initial experience.

An active-self IA

- An approach in relating excteroceptive and proprioceptive data:
- I cause something to happen in myself to see the effect over the course of time in the world outside
- Taking control data as proprioceptive sensory/cause/control/evidence data and position as exteroceptive sensory/effect/state data

An active-self IA

- A drone that knows how much it's position changes in space if it increases 10% of it's front rotors

How to mathematically model - Bayesian Networks (BNs)

- BNs are probabilistic models which model the probability of occurrence of an event conditioned on occurrence of some evidence.
- This builds the cause-effect section of a temporal, cause-effect model
  - In the example in previous slide, this can be interpreted by the a drone as "How much change in position may I experience if I increase my front rotors' power by 10%"
- DBNs take time into consideration by predicting an event not only based on the evidence but also based on the previous state of the IA
  - If the previous drone not only knows how much power it has added to its rotors but also what its current position is, then it can estimate its next position

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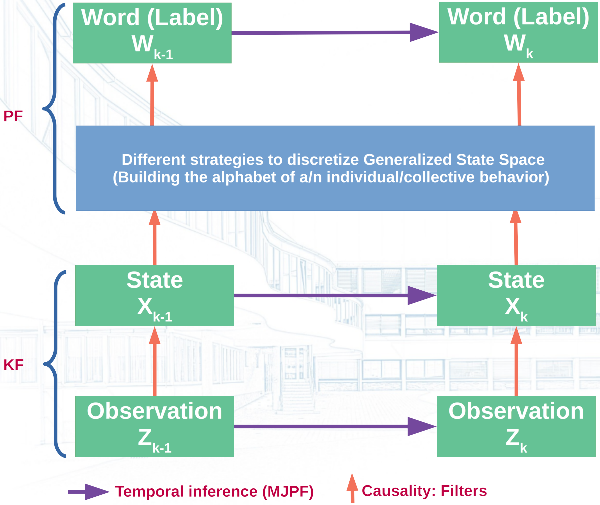
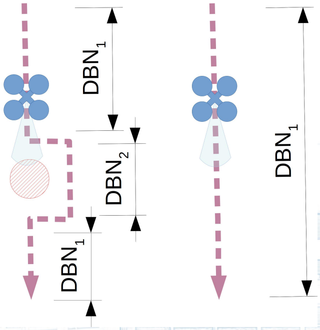
How to mathematically model - Filtering

- No (mobile) intelligent agent can never know what its true state is in continuous state space it can only estimate its state. A bank of Kalman filters can map the observation to continuous state space.
- Known experiences of words of a dictionary can be composed of known alphabets. These alphabets can be built based on different strategies, but all should start by discretizing the (generalized) state space.
- Now we need another filter to map continuous estimated (generalized) state to meaningful(known, already seen) regions. To do this a bank of Particle filter can be used.

How each DBN look like - Markov Jump Filter Model



Example

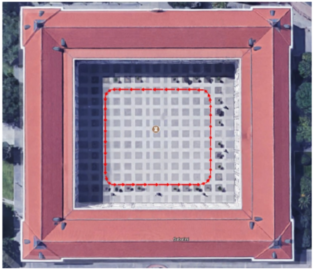


The models choice

- The choice of other the right DBN to practice is teh subject of another study but some research group are working on ideas from scientists such as Karl Friston[1]

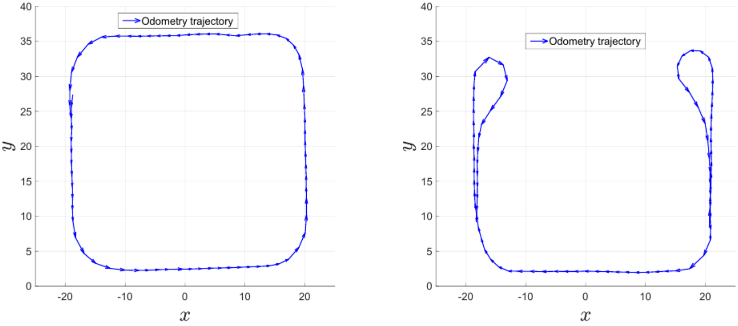
[1] Friston, K. J. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, *11*, 127–138.

An example of previous works



Kanapram, D., Campo, D. A., Baydoun, M., Marcenaro, L., Bodanese, E. L., Regazzoni, C. S., & Marchese, M. (2019). Dynamic bayesian approach for decision-making in ego-things. *2019 IEEE 5th World Forum on Internet of Things (WF-IoT)*, 909–914

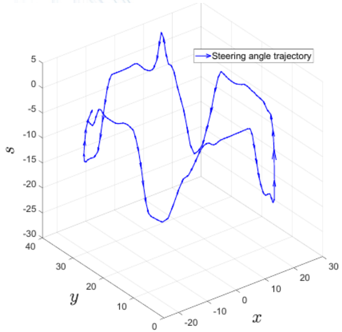
An exemplary previous work



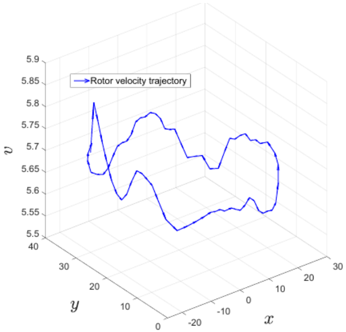
(a) Perimeter monitoring

(b) U-turn

An exemplary previous work

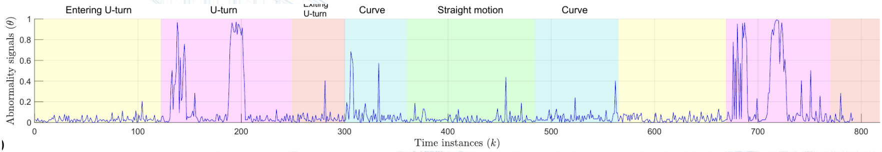


(a) Steering w.r.t position data



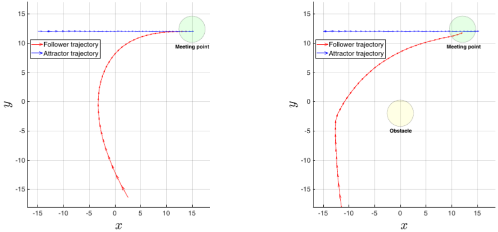
(b) Rotor velocity w.r.t position data

An exemplary previous work



Collective SA

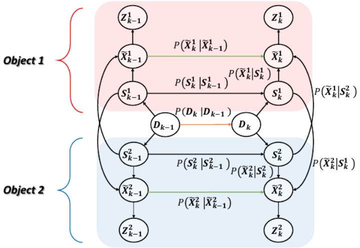
Can the same studies happen for the course of relationship between IAs? In Baydoun, M., Campo, D., Kanapram, D., Marcenaro, L., & Regazzoni, C. S. (2019). Prediction of multi-target dynamics using discrete descriptors: An interactive approach. a solution is proposed. Force fields represent the normal course of relationship which should be maintained between two agents



(a) Normal interaction data (b) Abnormal interaction data

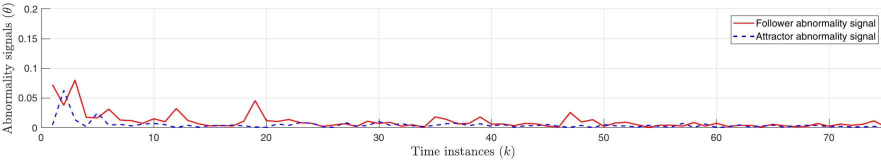
Collective SA

A coupled, multilevel, switching DBN to describe the relationship



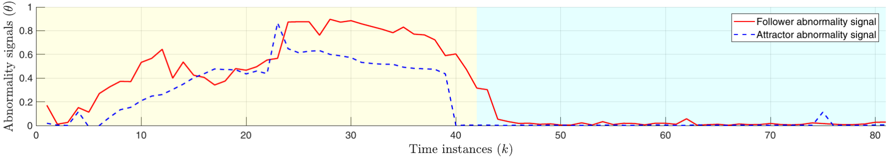
Collective SA

Abnormality signals



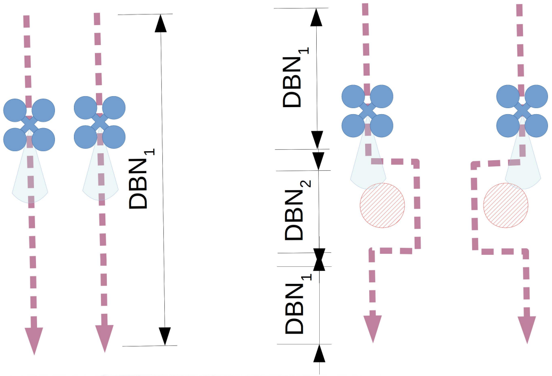
Collective SA

Abnormality signals



Collective SA - Future plan

As a future effort we seeks to apply the same idea for formation control of multiple drones



References I

Baydoun, M., Campo, D., Kanapram, D., Marcenaro, L., & Regazzoni, C. S. (2019). Prediction of multi-target dynamics using discrete descriptors: An interactive approach.

Friston, K. J. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, *11*, 127–138.

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