Primitive thoughts on Self-aware collective areal transportation - version 0.1

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1 Abstract

(The abstract should be changed) This proposal takes a collective self-aware approach to prove that semantic-awareness improves better decision making with regard to maintaining homeostatic state of swarms who should transport a load. Self-awareness which is considered here as the ability of an Intelligent Agent to recognize abnormality from its initial knowledge and build, memorize and retrieve new dynamic models out of high abnormalities for further use. Semantic-awareness in this proposal is equal to Level 1: Understanding the dynamic models other agents are reviewing now and Level 2. Understanding the difference between same models appearing in different contact (i.e previous model and future model). This proposal plans to prove that the higher the level of semantic-awareness is, the better collective behavior is achieved in a local communication scheme in which agents are allowed only to communicate with neighboring agents. That is, better generative/descriminative and abnormality detection models will be generated which will result in emergence of improved collective behavior.

2 Introduction

3 Force field

4 Motivation

Scientific

- Does semantic-awareness improve existing multi-robot self-aware trajectory tracking?

Technical

- Collective load transportation
- Collective load landing

- Application of Micro UAVs because of their low inertial value which cause less damage during

5 Objectives

Short term Improving the state of the art by any means

Long term Developing a Bayesian based, self-aware framework such that it can

- Make a distinction between the abnormalities raised from a new experience or those from minor disturbances (Disturbance rejection)
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6 Problems which should be solved

- Formation control
- Path planning
- Trajectory tracking
- Disturbance rejection
- Collision avoidance
- State estimation
  - Sensors
- Formation control approach

7 Possible ways to improve the state of the art

- Swarm intelligence
  - Semantic, local communication
  - Training a model to map locally emergent individual behavior to collective behavior
    - Individual behavior is modeled in papers such as Kanapram et al. (2020) to collective behaviors described in Baydoun et al. (2019)
- Taking a leader-less or leader variant approach
  - Leader will be changed according some kind of privileged such as its closeness to the destination or being positioned such that better degree of data(information) access is provided

From sensing to building words of individual quasi-constant motions such as Kanapram et al. (2020) to collective behavior describe with languages such as Baydoun et al. (2019)

8 Related work and state of the art

Collective adaptive systems

Collective object transportation

Existing object transportation with multi drone systems Jackson et al. (2020)

Existing drone swarm navigation models in tight spaces Soria et al. (2020)

Swarm flocking Vasarhelyi et al. (2014)

Swarm collective behavior through local communication

Self-organizing swarms

Self-organizing drones

Dynamic systems modeling

Discretization of continuous features

Dynamic Bayesian Models

Semantics

Semantics in dynamic systems

In action sequences

in natural language

9 Methodology

From individual perception to collective behavior : The methodology must cover from the simplest

- Individual perception of environmental data
- individual decision making
- creating individual generative models
- creating generative interaction model for each triples of agents with consecutive rankings (agents are aware of existence of the behind and front agents)
- messaging to neighbors through individual generative models
- creating individual descriminative model in which a messaged individual generative model and the rank of the sender may cause a decision and an action
- Collective behavior

Overview The experiment takes a collective self-aware approach in the sense that it will be first trained by an initial generative model for a reference task and then new generative and descriminative models will be generated from the data presenting the observed abnormality. The modeling starts from initial modeling of collective movements of a straight flight from one point to another and then introducing the initial flight path with obstacles such as tight flight corridors which may need a collective maneuver or column avoidance which needs a single maneuver to avoid the obstacle. From these new experiences, new models should be generated and through neighboring interactions other agents should learn to decide a reaction according to the communication. The goal of this proposal is to prove that if such model messages is transmitted locally but contextually, then some improvments will be observed in comparison to the base models.

9.1 Hierarchical Homeostatic state

In thus proposal, homeostatic state is the generalized state in which the dynamic systems has the highest survival chance and comes at two levels in this proposal

1. Trying to keep individual abnormality signal possible
2. Avoid individual collision
3. avoid load collision
4. Trying to keep the collective abnormality signals minimum according to the currently practicing generative model

5. Returning back from the current interaction model to the reference interaction model (a regular, 2d convex) as soon as possible which might be one of the following tasks

9.2 Generative models

Two generative models should be considered. One which defines

Interaction model The necessary changes in the course of orientation vector that each two consequent ranked agents should keep according to perform each maneuver such as those in the scenarios in Section

Individual model The trajectory which each individual agent is supposed mov

Discretization As a further phase, to avoid computational complexity, such models should be learned by dividing the environment to discreet regions in which mutual relation dynamism is approximately constant and such models should be trained for consecutively ranked agents and not between all agents.

9.3 Discriminative models

The models which are responsible to attribute a sequence of observations with the best fitting generative model.

For collective behavior

For individual behavior

9.4 Abnormality detection

Feature selection

Sources of abnormality detection

9.5 Generative/Descriminative Model creation

After abnormality detection, the sequence of data which represents the abnormality should be used for training a dynamic generative model.

9.6 Semantic awareness

Semantic means the signification relationship between a sign and a signified. Accordingly,semantic-awareness is the ability to correspond signs to signified entities. This ability embodies in

- Cause(sign)-effect awareness (Models mostly by Bayesian inference/reasoning)
- A sign can refer to signified entities such as actions, entities etc

such ability in an artificial intelligent agent must arise

- reactions

which may ultimately result in reactions

- improvement in homeostatic situation of an agent

So this is the process

1. emergence of a sign
2. corresponding it to a signified
3. action

Construction of a language Discreetizing generalized state space such that from (some) **new composition of different segments** new semantic(signified entities) arises. If the no dicreetized segments composition arises any meaning, then no language is built. these meanings may refer to

- Existing signified entities (maybe in the generalized state space)
- A semantic piece of collection behavior 9.6.1

Is the matter of building a language which is understandable by all agents. Mostly, the alphabet of such language is based on discretizing the generalized state space (by clustering methods such as Fiser et al. (2013), Kohonen (2001)) such that motion remains relatively constant. Generalized space can be used

Language to describe dynamism of individual generalized state spaces (individual semantic awareness) Kanapram et al. (2019) offers an exammplary method is to cluster the data for each time dervitave order of generalized state space and uses the centroids of each cluster as the representative of that cluster. These representatives form the alphabet with which words representing different generalized state spaces can be introduced by different composition of such alphabets i.e, in a moving object different positions, velocities and alterations are clustered into different classes and different composition of centroids of a position class, a velocity class and an alteration class builds a word. Such word could be transmitted to neighboring nodes to describe a reviewed, practicing or predictable experience.

9.6.1 Language to describe dynamism of interaction (collective semantic)

Baydoun et al. (2019) suggests a language in which alphabets are formed of clustered regions in generalized state spaces of individual dynamic agents while coincidence of such regions by all agents in the network form the vocabulary.

9.6.2 From individual behavior to collective behavior

Deals with the problem of contribution of local individual behavior in emergence of collective semantics.

9.6.3 Synchrony and diachrony

Whether the vocabulary is describing individual or collective agents behavior, in each language previously experienced generalized state can represent the past, currently experiencing generalized state can represent now and predicted generlized state can represent the future tense along the diachrony (horizontal) of the forming language. On the other hand, the distance between classes from which such words come from, can model the synchrony of the language.

9.6.4 The question

Now the question is how such semantic awareness improves

- Abnormality detection
- New generative model creation
- Discriminate between generative models
- Improving decision making and control

For example if a drone receives a message with a different sematic vector, how should it react to it with its actuators? **But the most important thing is that, does semantic awareness improves performance of the discriminative models by which the agent chooses the best matching generative model according its observation?** In a semantic-aware multi agent system, observation is composed of

- the data derived from its exteroceptive and proprioceptive sensors
- the semantic messages it receives other (in this case neighboring) agents.
- The rank of the sender agent

One study possibility is that which sequence of individual motion (words) means (is the evidence) for which collective word (behavior)

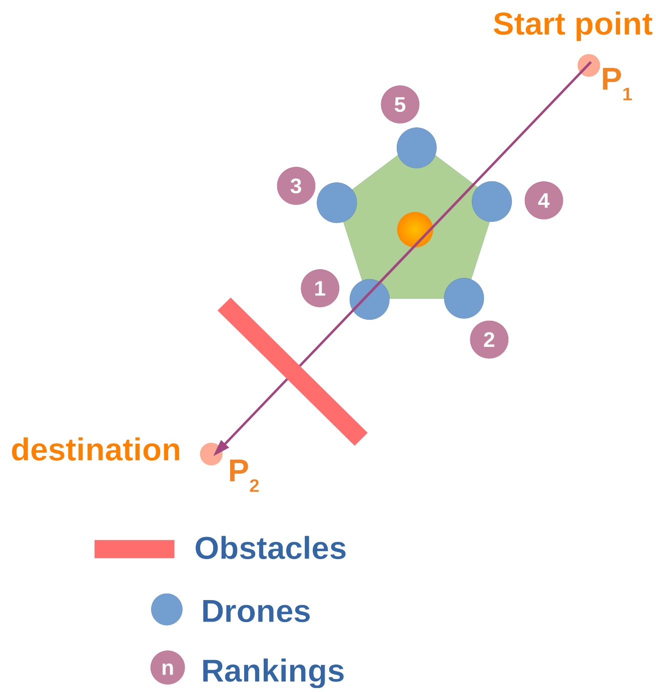

Figure 1: Closer agents to the destination take the lead. If destination of two agents is measured to some degree of tolerance equal, then random ranks will be assigned. Semantic stated interaction is only allowed between consecutive neighboring ranks.

9.7 Neighboring agents and Ranking

The one which is closer to the destination will be ranked lower and the ranking starts from 1. The leader is rank 1. The leader is rank one.

9.8 Communication

Communication rules The goal of the rules are to define a notion of neighborhoodness for the agents.

- No agent can transmit the generative models from other agents to the neighboring agent.
- Messages can be made of one generative model and the senders rank or more than one (for distributional semantics)
- Messages can only be transmitted to neighboring ranked nodes when the generative model an agent is practicing changes.

9.9 Sensors

Exteroceptive

- Environment
- From neighboring agents

Proprioceptive

- Gyroscope: For measuring pitch, role, yaw
-

Heterogeneity Heterogeneity of the sensors which plays the heterogeneity for the whole system will be sought in deployement of different sensors installed independently on different agents.

Contextuality

- Active self
- Passive self

Multi-sensory approach / Fusion

Feature selection for generative and discriminative models Choosing the best set of features which captures metrics such as abnormality

Sensor precision

9.10 Decision making and control

- A model to convert abnormality signals to decisions for actuators
  - To return back the system to the best fitting, existing generative model by simultaneously making decisions that minimize the deviations from that model
  - Continuously trying to return back to the reference generative model this reference model defines the homos static state to which the whole system tries to return

10 Experimental setup

This section, contains scenarios for which DBN models should be trained. Having these models trained, then whatever solution is decided, then it should improve

- Predictive model selection
- Generating predictive models
- Decision making to decrease abnormality rate (the difference between the state prediction of practicing models and state observation) which must result in better trajectory tracking models

Each scenario, is in fact, a predictive model.

10.1 Rigidly attached

The size of drones is continuously reducing which helps with better attaching them to the body of the load, similar to collective transportation in ants. This approach brings more flexibility to collective transportation.

Reference scenario

- M_1 Taking off
- M_2 Tracking a straight trajectory from point A to Point B
- M_3 Landing

Scenario: Horizontal obstacle avoidance

Scenario: Vertical obstacle avoidance

Scenario: Turning

10.2 Suspended pay-load

Minimum experimental requirements

- As many MAVs such that neighboring communication is meaningful
- Minimum two sensors to establish a relationship between heterogeneous sensors. The best of such sensors for depth and obstacle selection in low speed are active sensors (Apatean et al., 2007):
  - Lidar
  - Sonar
  - Radar
  - IMU

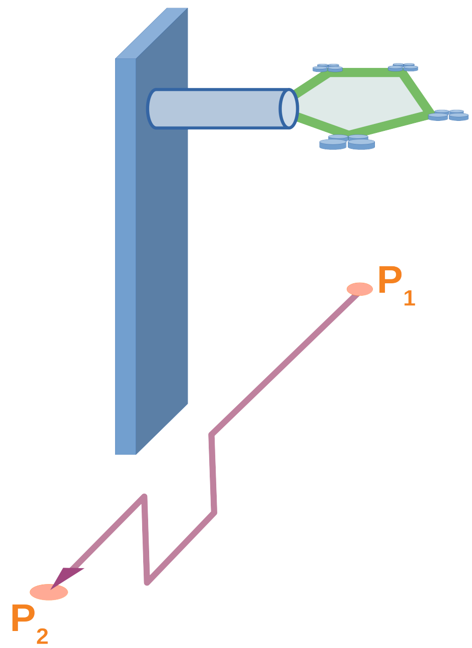

Figure 2: Collective horizontal obstacle avoidance

10.3 Scenarios

In this section several scenarios will be presented from which both generative individual and interaction models can be learned some of these scenarios entail generalized state change from the agents while others don't. For each of these scenarios, a DBN model should be learned. Then we should prove that semantic messages composed of at least two individual generative models which represent the previous reviewed generative model and the current one improves the baseline model which only considers reception of current practicing DBN by the neighboring node.

Reference collective horizontal movement See Figure 5

Reference collective vertical landing See Figure 6

Collective horizontal frame passage (Important because it could approximate any complex surface by variational shape approximation techniques such as Cohen-Steiner et al. (2020)) See Figure 7 for a few samples of similar scenarios for which collective interaction models must be built.

Collective vertical frame passage Similar to "Collective horizontal frame passage" scenarios, but the frames are places vertical

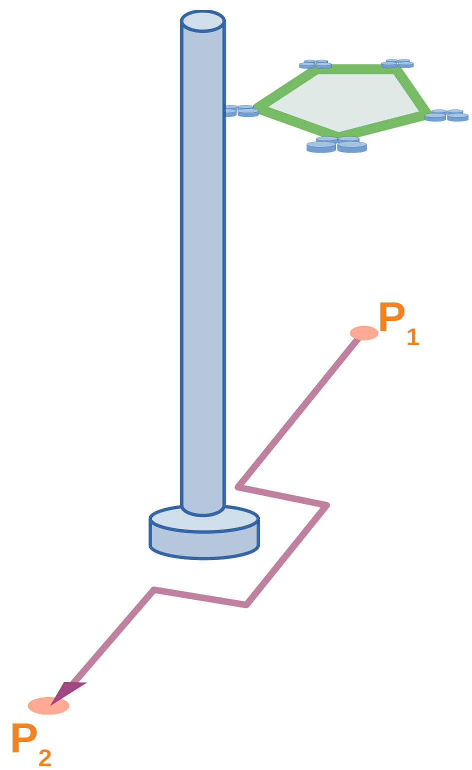

Figure 3: Collective vertical obstacle avoidance

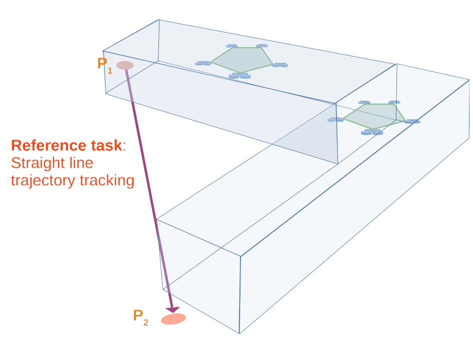

Figure 4: Reference task for which an initial model should be learned

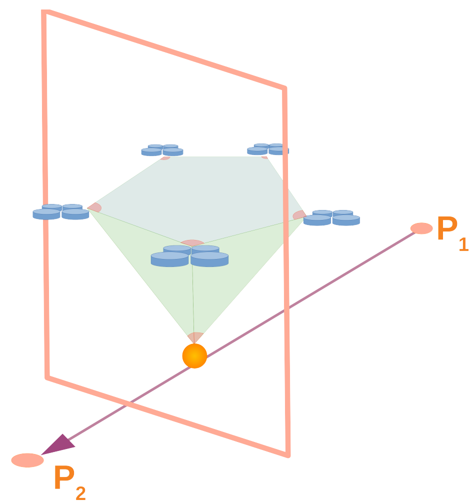

Figure 5: Reference task for which an initial model should be learned

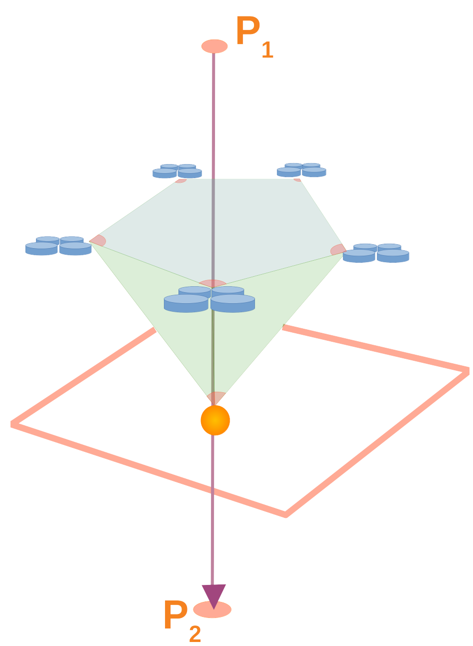

Figure 6: Reference task for which an initial model should be learned for vertical landing

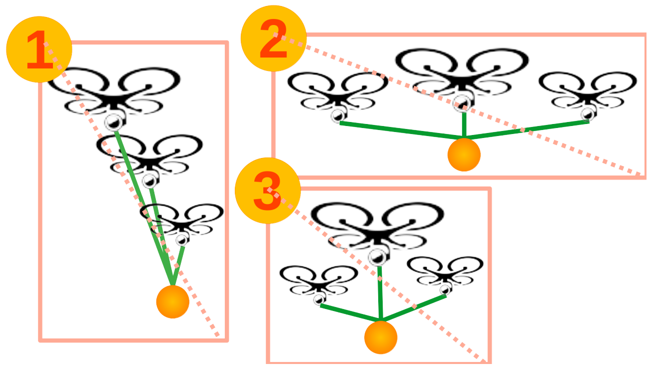

Figure 7: Exemplary scenarios from which

Vertical column avoidance A scenario in which changes in generalized state of one agent does not entail changes in other agents. See Figure 8

Horizontal column avoidance A scenario in which changes in generalized state of one agent does not entail changes in other agents. See Figure 9

Scenario: Horizontal column avoidance with collective shift This scenario can represent a set of scenarios in orientation vector between neighboring agents does not change but a collective shift is required.

11 Papers

Conferences

Journals

- Journal of advanced transportation [1]

References

Anca Apatean, Alexandrina Rogozan, Corneliu Rusu, and Abdelaziz Bensrhair. Sensors for obstacle detection - a survey. pages 100 – 105, 06 2007.

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

David Cohen-Steiner, André Lieutier, and Julien Vuillamy. Lexicographic optimal homologous chains and applications to point cloud triangulations. 2020.

[1] `https://www.hindawi.com/journals/jat/`

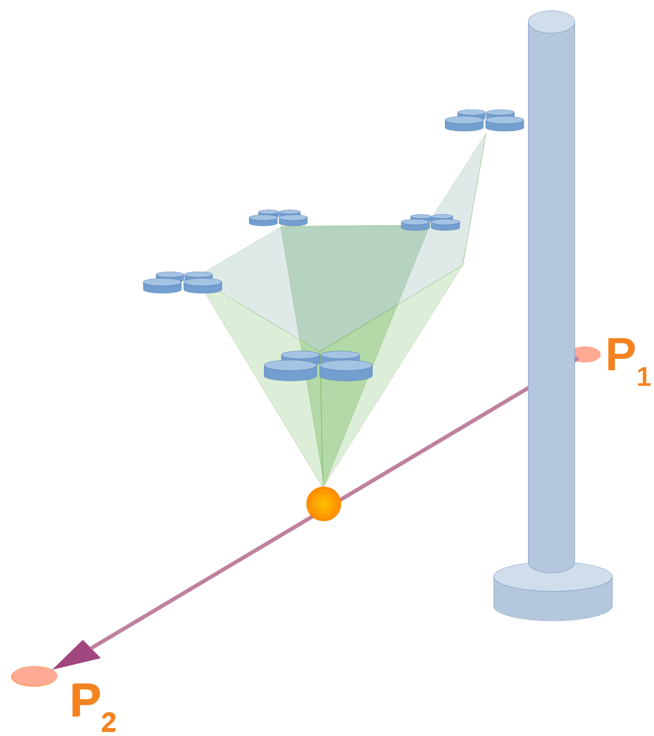

Figure 8: Vertical obstacle avoidance

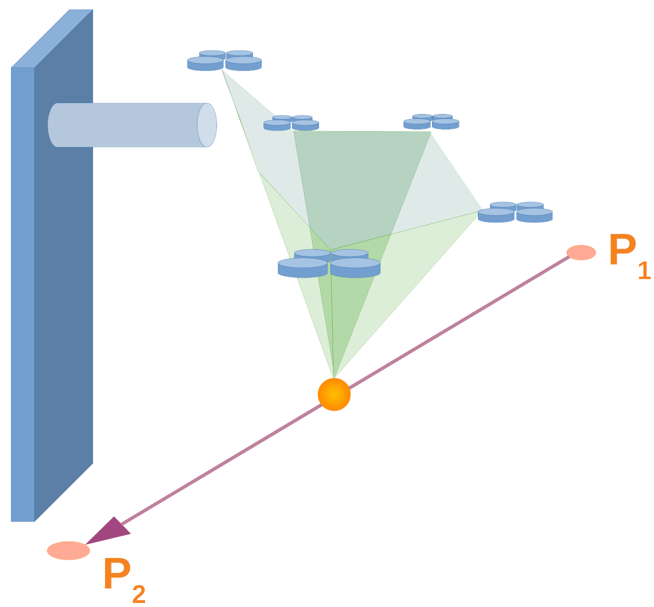

Figure 9: A scenario similar to Figure 8 from which collective behavior could be learned

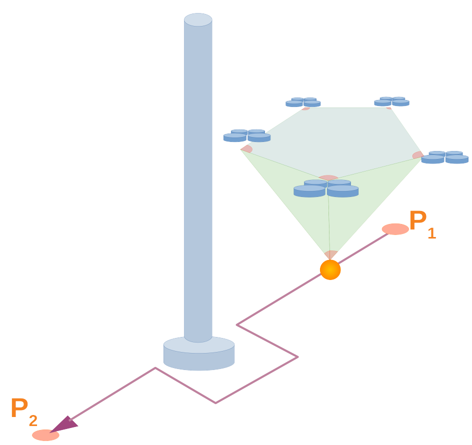

Figure 10: Collective movement in open space which requires collective movements

Daniel Fiser, Jan Faigl, and Miroslav Kulich. Growing neural gas efficiently. 2013.

B. E. Jackson, T. A. Howell, K. Shah, M. Schwager, and Z. Manchester. Scalable cooperative transport of cable-suspended loads with uavs using distributed trajectory optimization. *IEEE Robotics and Automation Letters*, 5(2):3368–3374, 2020.

Divya Kanapram, Pablo Marin-Plaza, Lucio Marcenaro, David Martin, and Carlo Regazzoni Arturo de la Escalera. Cognitive dynamic systems: Perception-action cycle, radar and radio. 2019.

Divya Kanapram, Fabio Patrone, Pablo Marín-Plaza, Mario Marchese, Eliane L. Bodanese, Lucio Marcenaro, David Martín Gómez, and Carlo S. Regazzoni. Collective awareness for abnormality detection in connected autonomous vehicles. 2020.

T. Kohonen. Self-organizing maps. *Springer Berlin Heidelberg*, 2001.

Enrica Soria, Fabrizio Schiano, and Dario Floreano. Swarmlab: a matlab drone swarm simulator. *arXiv preprint arXiv:2005.02769*, 2020.

Gabor Vasarhelyi, Csaba Viragh, Gergo Somorjai, Norbert Tarcai, Tamas Szorenyi, Tamas Nepusz, and Tamas Vicsek. Outdoor flocking and formation flight with autonomous aerial robots. 02 2014.