Prediction of multi-target dynamics using discrete descriptors: An interactive approach

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Introduction

Moving objects can be modeled as a series of ***interactions*** with their surroundings such that their dynamics are a result of ***forces*** (external effects) that act on them over time [1]. Forces that act over objects can be ***attractive*** or ***repulsive***. Goals, i.e., destination points, can be represented by attractive forces and obstacles, i.e., structures or other entities, as repulsive forces [2]. Our contributions are listed as follows:

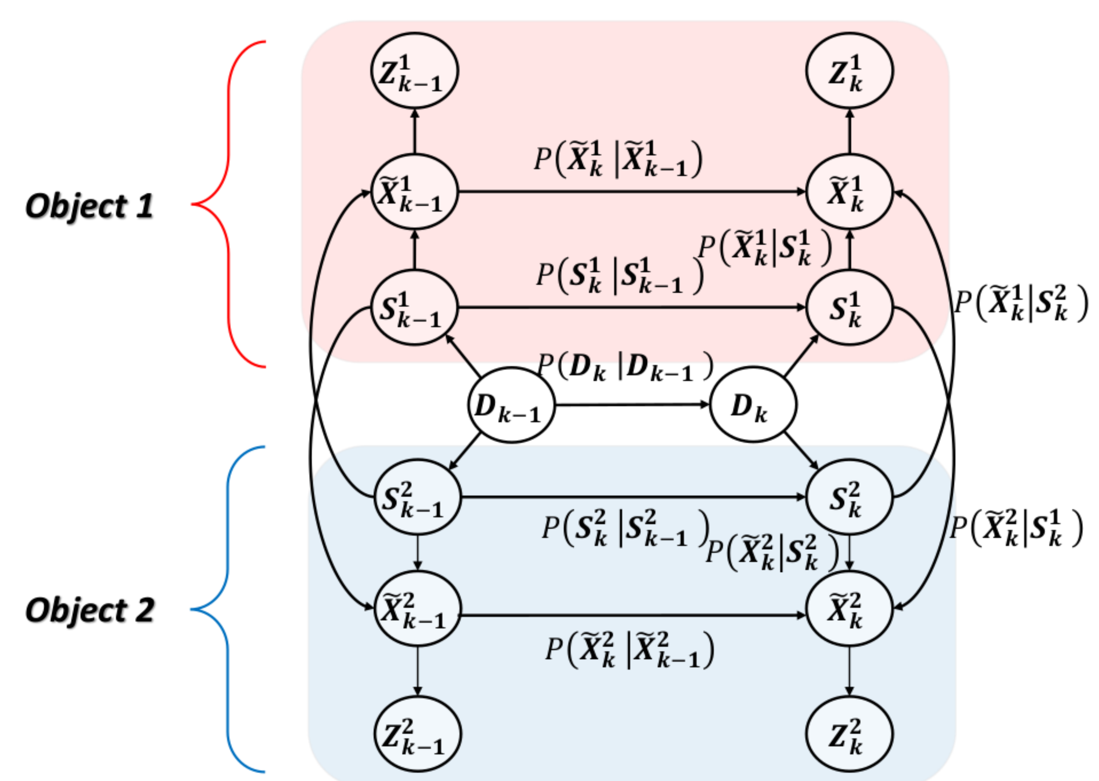
- Modeling of ***conditional dependencies*** between dynamical objects
- Employing a ***coupled Dynamic Bayesian Network*** (DBN) structure
- ***Detecting abnormalities*** based on identified interactive effects

Proposed method

1. Definition of coupled generalized states: For a moving object i, let us define its internal state at a time instant k as $\tilde{X}_k^i = [\boldsymbol{x}, \dot{\boldsymbol{x}}]^T$. In case of analyzing the joint motion of two objects $i = \{1,2\}$, let us define the coupled generalized state:

$$\tilde{\boldsymbol{X}}_k = \left[\tilde{X}_k^1,\ \tilde{X}_k^2\right]^T.$$

2. Learning of coupled DBN:
   - Learning vocabularies for $i = \{1,2\}$.
   $$\boldsymbol{S}^i = \{s_1^i, s_2^i, \ldots, s_{L_i}^i\}.$$
   - Learning dictionary.
   $$\boldsymbol{D} = \{D^1, D^2, \ldots, D^M\},$$
   $$D^m = \left[s_{l_1}^1, s_{l_2}^2\right].$$
   - Learn discrete transition model
   $$p(D_k | D_{k-1}, t_k)$$



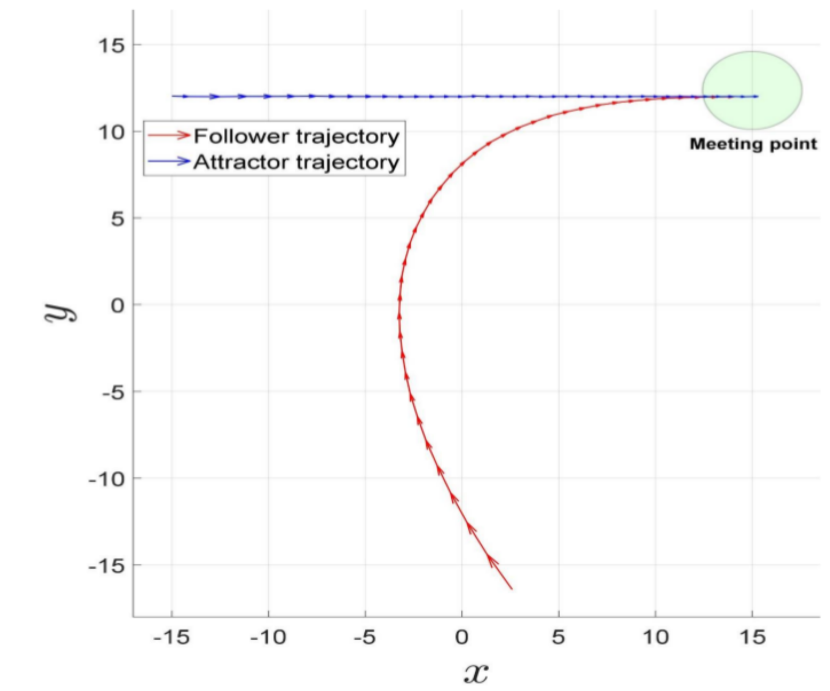
3. Online interaction tracking: A probabilistic switching model called ***Markov Jump Particle Filter*** (MJPF) [3]. This filter uses a ***Particle filter*** (PF) for inferring systems' discrete levels. Additionally, each considered particle employs a ***Kalman filter*** (KF) that tracks the generalized states of observed entities.

4. Abnormality measurement: This work proposes an abnormality measurement based on the ***Hellinger distance*** between predicted coupled generalized states $p(\tilde{X}_k^i | \tilde{X}_{k-1}^i)$ and the evidence $p(Z_k^i | \tilde{X}_k^i)$, such that:

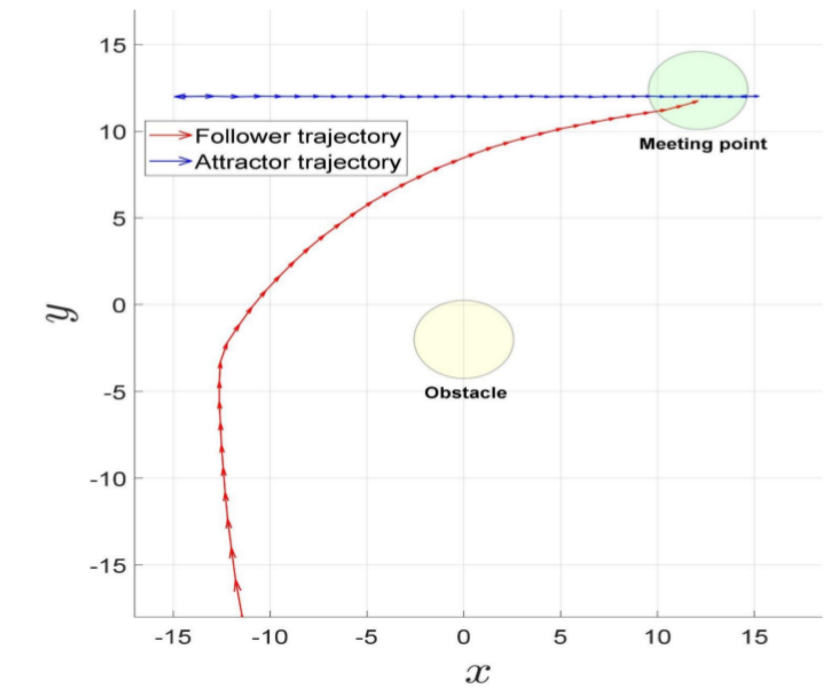
$$\theta_k^i = \sqrt{1 - \lambda_k^i}, \quad \text{where} \quad \lambda_k^i = \int \sqrt{p(\tilde{X}_k^i | \tilde{X}_{k-1}^i) p(Z_k^i | \tilde{X}_k^i)}\, d\tilde{X}_k^i.$$

Experimental results and evaluation

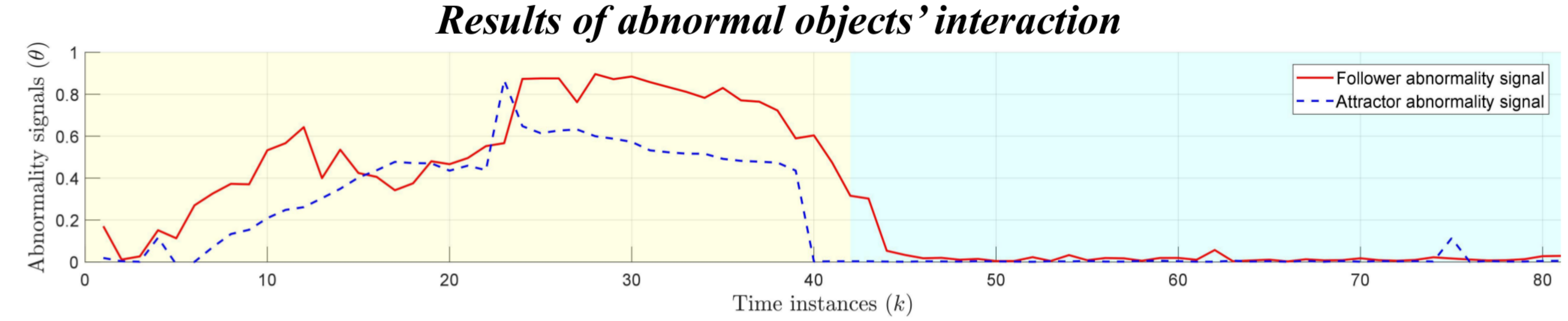
Sample of training data



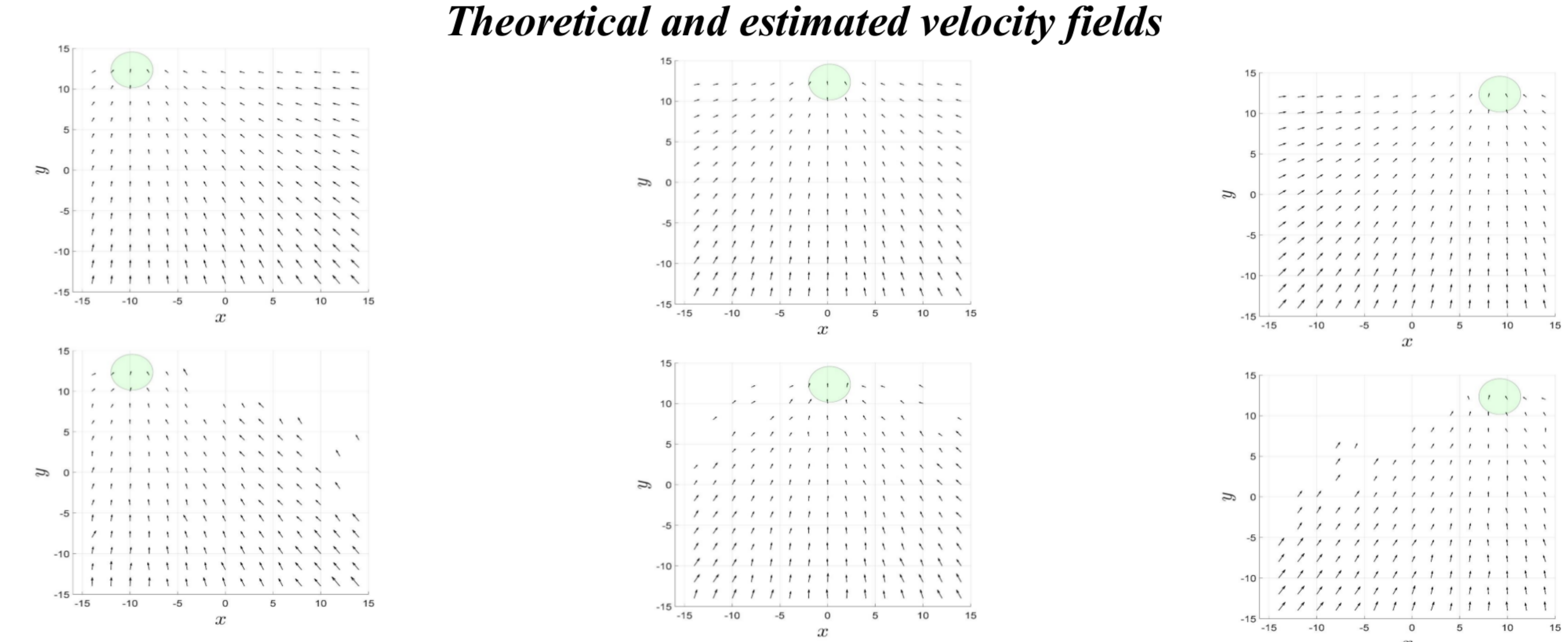
Sample of testing data



Results of abnormal objects' interaction



Theoretical and estimated velocity fields



Conclusions and future work

Attractive/repulsive forces are modeled inside a DBN structure that codifies normal behaviors of observed objects. Continuous and discrete variables are modeled by a PF coupled with set of KFs that enable to detect anomalies in different inference levels in an online fashion. Possible future works include characterizing more complex interactions where more forces/objects are involved and understand the interplay of real moving objects inside DBN structures.

[1] D. Campo, A. Betancourt, L. Marcenaro, and C. Regazzoni, "Static force field representation of environments based on agents nonlinear motions," Eurasip Journal on Advances in Signal Processing, no. 1, 2017.

[2] Xu Chen, Martin Treiber, Venkatesan Kanagaraj, and Haiying Li, "Social force models for pedestrian traffic state of the art," Transport Reviews, pp. 1–29, 2017.

[3] M. Baydoun, D. Campo, V. Sanguineti, Lucio Marcenaro, A. Cavallaro, and Carlo S. Regazzoni, "Learning switching models for abnormality detection for autonomous driving," in 21st International Conference on Information Fusion, FUSION 2018, Cambridge, UK, pp.2606–2613, July 10-13, 2018.