

Efficient Causal Discovery for Robotics Applications



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Introduction and Motivation

Causal analysis of complex and dynamical systems is extremely demanding in terms of time and hardware resources [1], particularly for autonomous robotics with limited hardware and real-time demands.

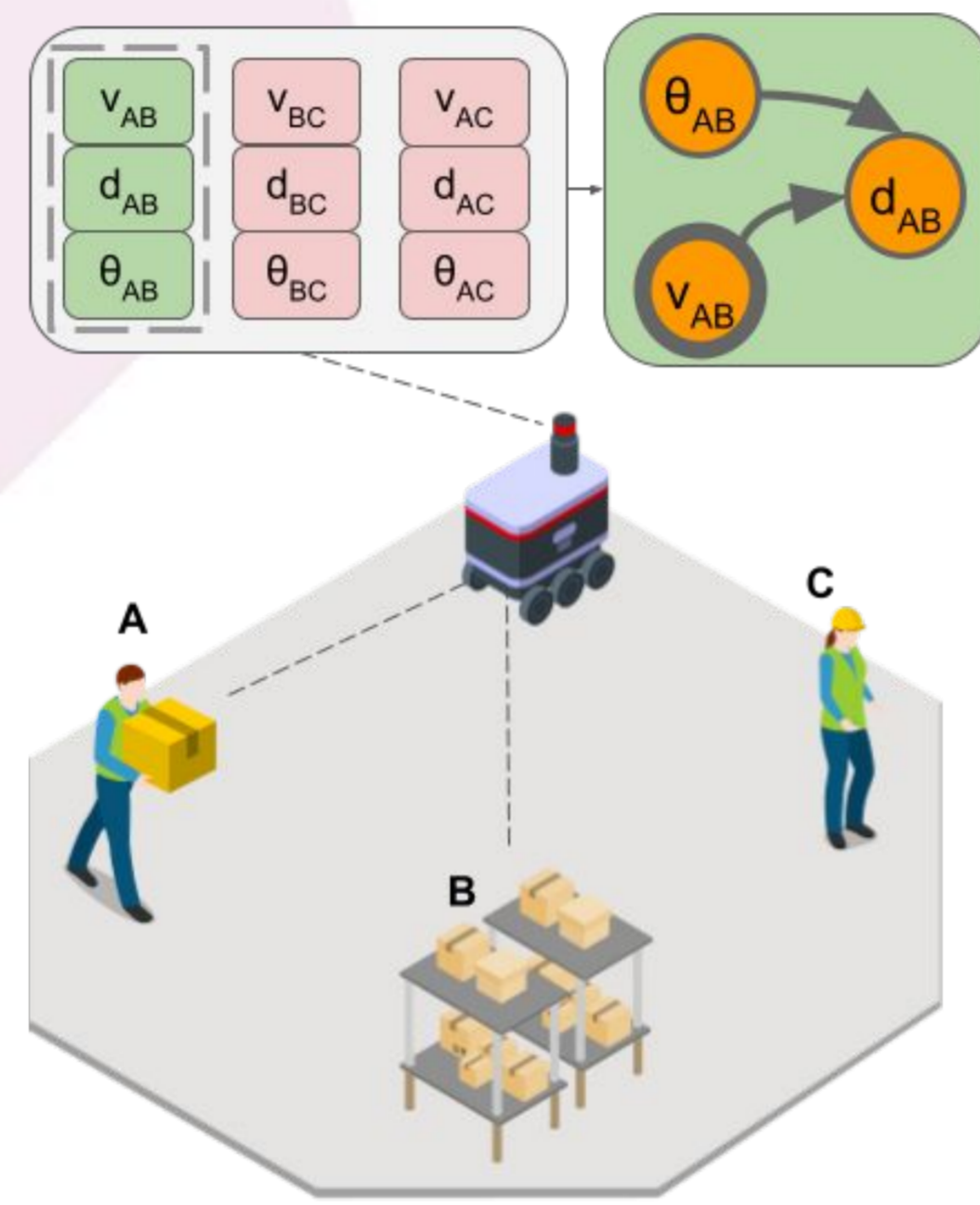
None of the existing causal discovery methods simultaneously extract crucial system features and establish causal connections among them while also considering execution time and computational costs necessary to accomplish the task.

Research objective:

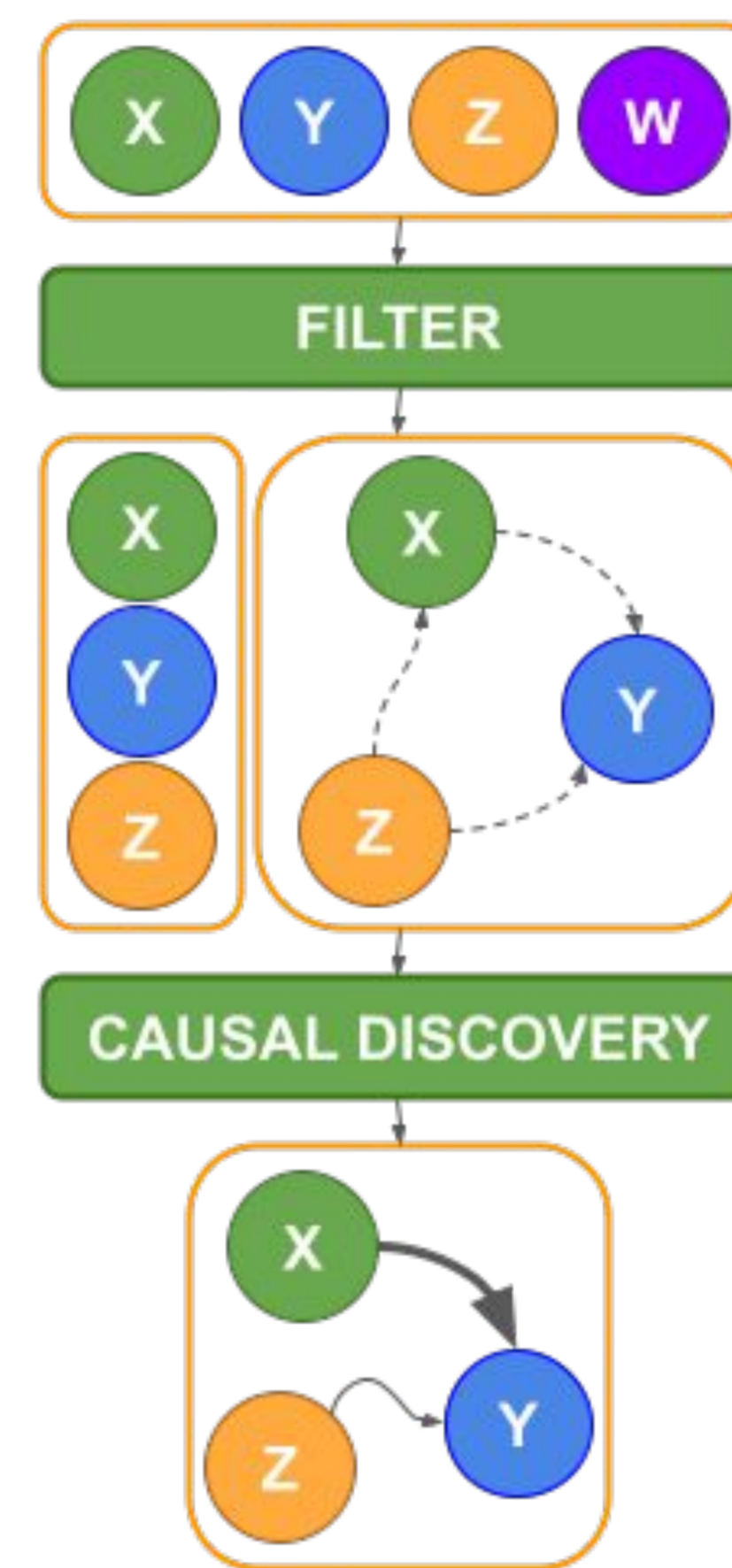
Develop an all-in-one algorithm capable of:

- identifying the most significant features from a predefined set of variables;
- constructing a causal model based on this selection.

This unified approach aims to optimise both speed and accuracy in causal discovery, making it more efficient and feasible for applications in robotics.



Filtered-based Causal Discovery

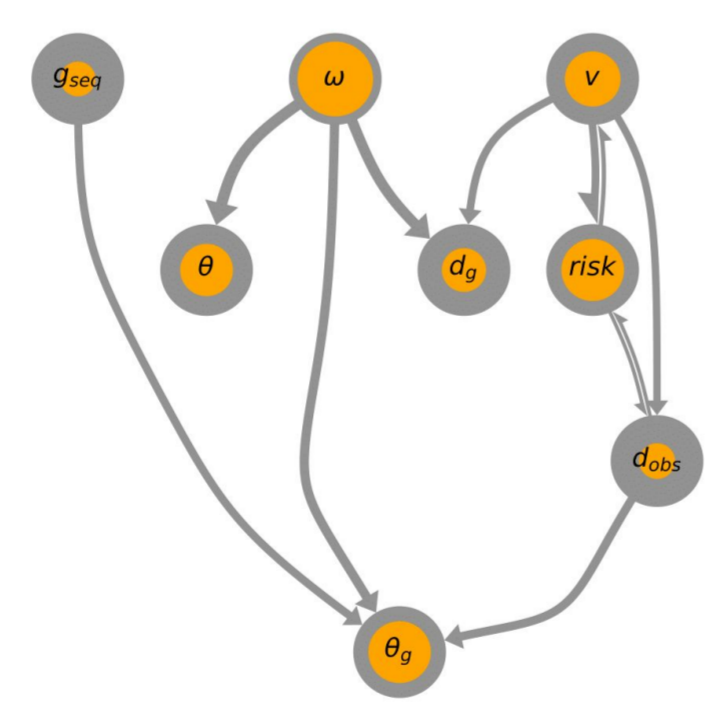
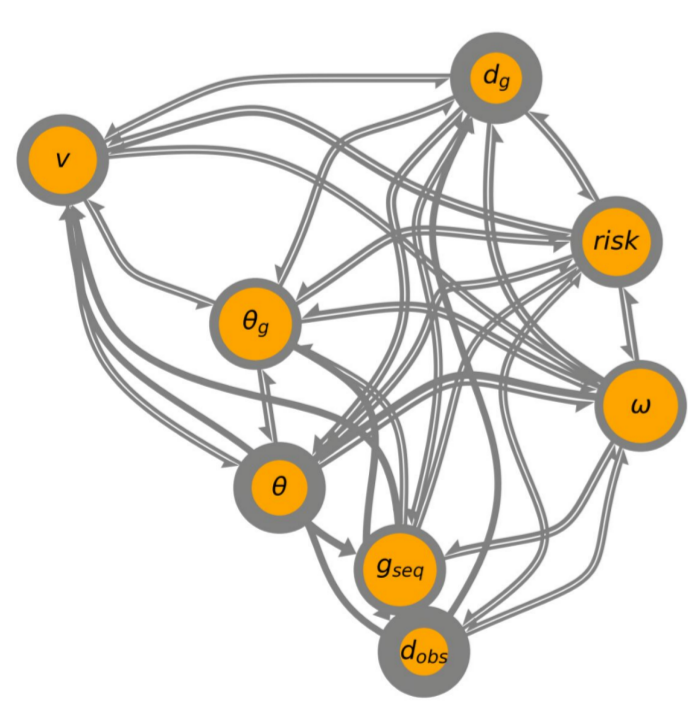
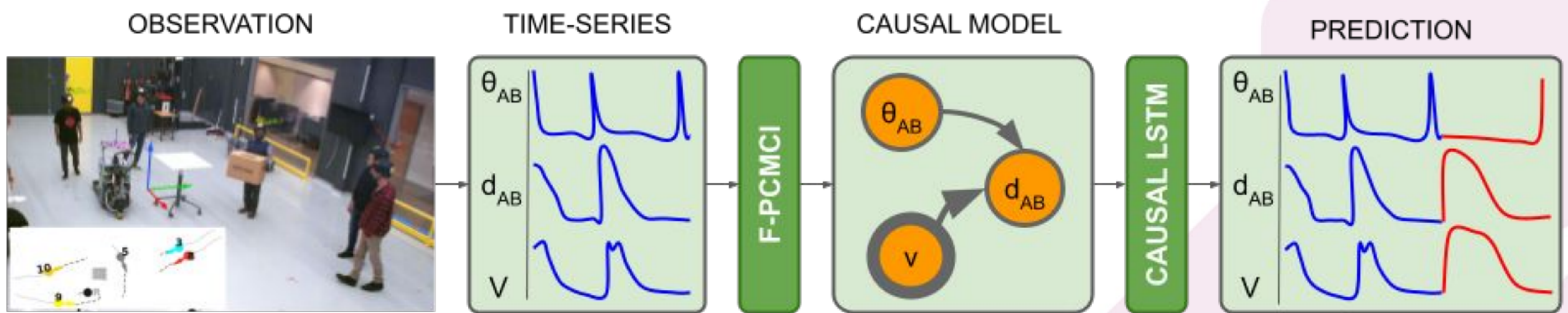


By using a Transfer Entropy (TE) filter, the Filtered PCMCI (**F-PCMCI**) [2] identifies significant features and possible associations between them, and based on them, builds a causal model. This strategy enables **faster** and **more accurate** causal discovery.

F-PCMCI steps:

- takes in input a prefixed set of variables;
- the TE-based filter analyses and removes irrelevant variables (e.g., constants or isolated ones). The reduced variable set is used to create a hypothetical causal model;
- the latter needs to be validated by a proper causal analysis, which is performed by the PCMCI causal discovery algorithm [1].

Robot Application and Results



We used our approach to model and predict spatial interactions, which involved three steps:

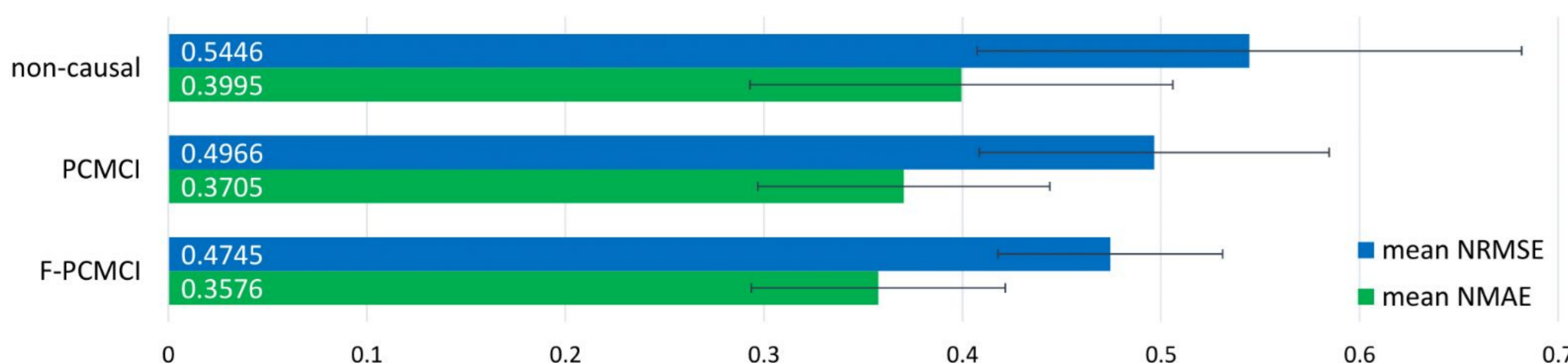
- extracting time-series of sensor data from human spatial interaction scenarios using the THÖR dataset [4];
- reconstructing the causal model using F-PCMCI;
- integrating the causal model in a LSTM-based prediction system.

To represent human spatial interactions, for each agent we considered 8 variables, inspired by [3]. These are the following:

- d_g distance to goal
- θ_g angle to goal
- v velocity
- ω angular velocity
- risk** collision risk, as proposed in [3]
- g_{seq} goal position sequence
- θ orientation
- d_{obs} distance to closest obstacle

PCMCI execution time 79'45"

F-PCMCI execution time 17'33"



References

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- [2] L. Castri, S. Mghames, M. Hanheide, and N. Bellotto, "Enhancing causal discovery from robot sensor data in dynamic scenarios," in *Conference on Causal Learning and Reasoning*, 2023.
- [3] L. Castri, S. Mghames, M. Hanheide, and N. Bellotto, "Causal discovery of dynamic models for predicting human spatial interactions," in *International Conference on Social Robotics (ICSR)*, 2022.
- [4] A. Rudenko, T. P. Kucner, C. S. Swaminathan, R. T. Chadalavada, K. O. Arras, and A. J. Lilienthal, "Thör: Human-robot navigation data collection and accurate motion trajectories dataset," *IEEE Robotics and Automation Letters*, vol. 5, pp. 676–682, 2020.



F-PCMCI

F-PCMCI

LSTM

Paper

