Enhancing Causal Discovery from Robot Sensor Data in Dynamic Scenarios

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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], making it a challenge for autonomous robotics with limited hardware resources and real-time requirements.

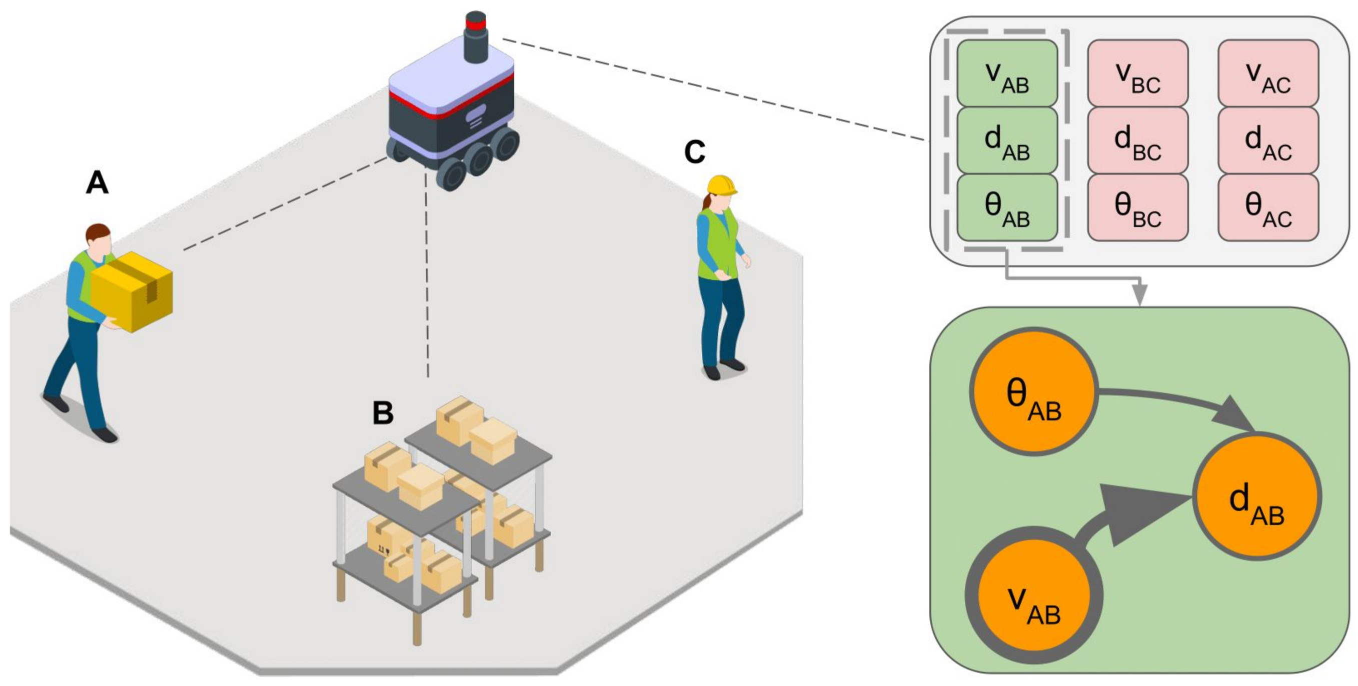
None of the state-of-the-art approaches extracts both the important features representing the system and the causal association between them, while at the same time taking into account the execution time and the computational cost for completing the task.

Research Objectives

Create an **all-in-one** algorithm able to:

- select the most meaningful features from a prefixed set of variables
- build a causal model from such selection

in order to enhance speed and accuracy of the causal discovery and make it more efficient and feasible for robotics applications.



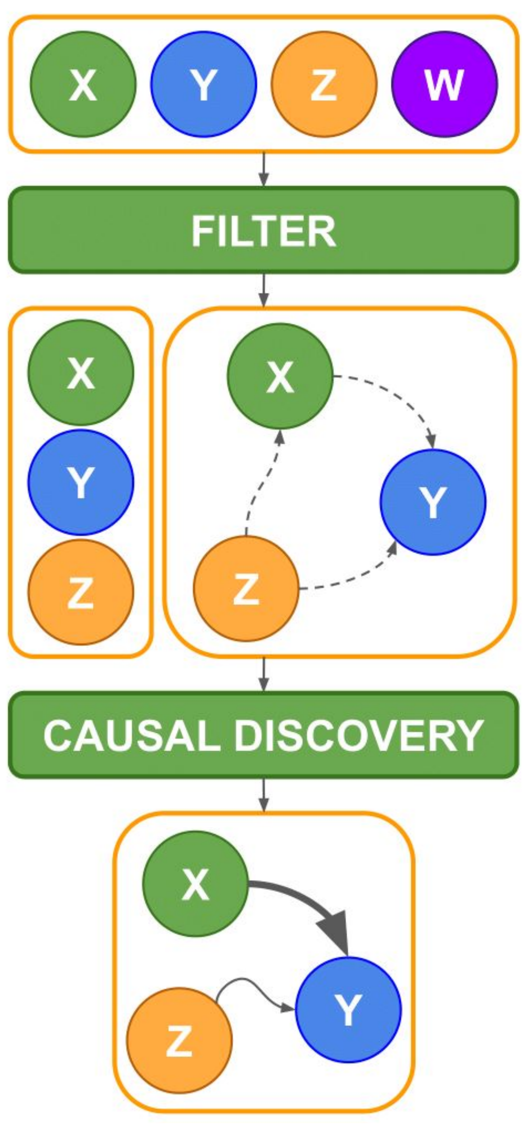
Filtered PCMCI (F-PCMCI)

Filtered PCMCI (**F-PCMCI**) identifies the causal features representing the system and, based on them, builds a causal model directly from time-series data. As a consequence, the causal discovery process turns out **faster** and **more accurate**.

It uses a Transfer Entropy (TE)-based method [2] to "filter" the important features and their possible associations from the whole set of variables, before the actual causal analysis.

More in detail, F-PCMCI performs the following steps:

- takes in input a prefixed set of variables;
- the TE-based filter analyses the set of variables and removes those unnecessary for the causal analysis (e.g. constant or unconnected variables). The shrinked set of variables is then used to build 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].



F-PCMCI GitHub repository

PCMCI vs F-PCMCI

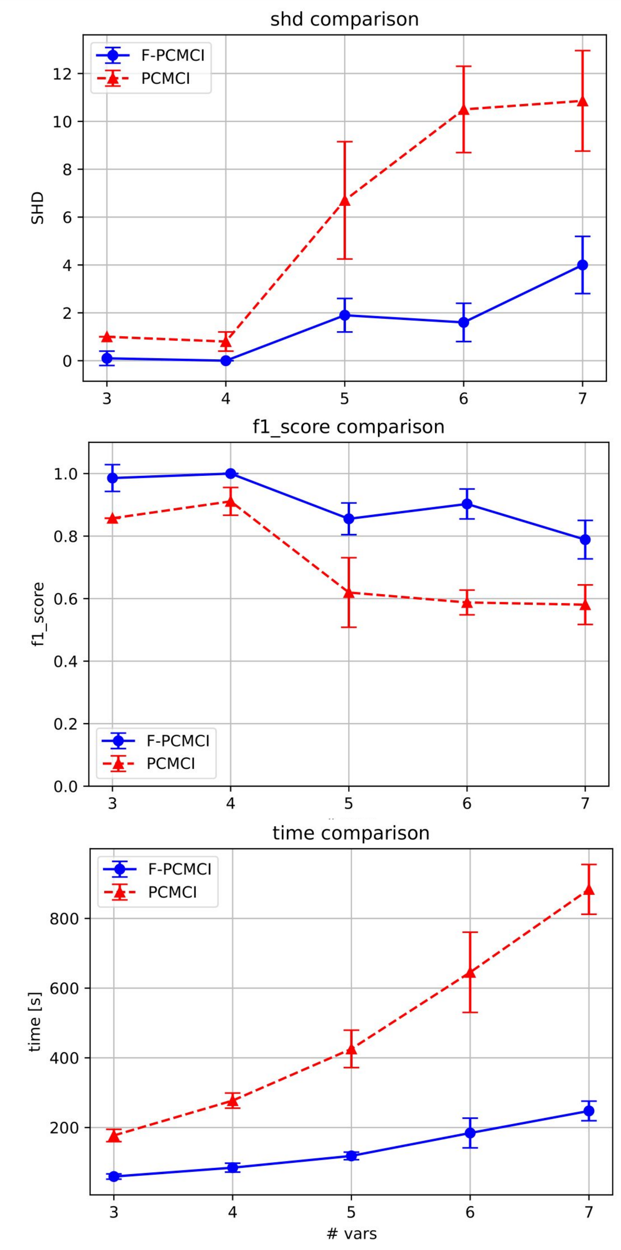
The correctness of our approach was evaluated based on toy problems, i.e. system of equations, with known ground-truth causal models.
Various types of dependencies:

- linear and non-linear cross- and auto-dependency;
- noise-only equations;
- independent and dependent equations;
- different time-lag dependencies.

The analysis was carried out considering a number of system variables varying between 3 and 7.

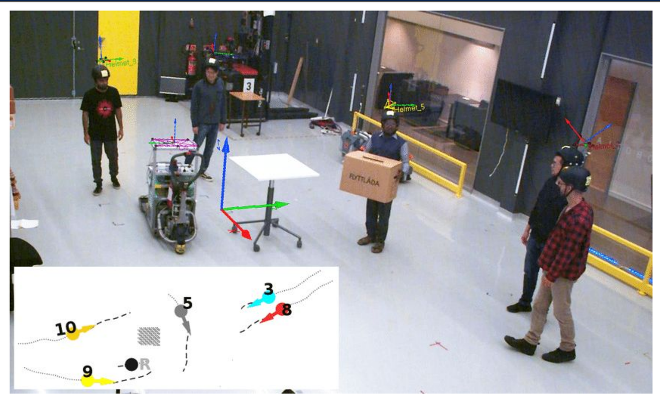
For each configuration, we performed 10 run tests with random system coefficients, using as evaluation metrics the mean over all the tests of

- Structural Hamming Distance **SHD**
- **F1-score**
- **execution time** (in secs).



Modeling Real-world Human Spatial Interactions

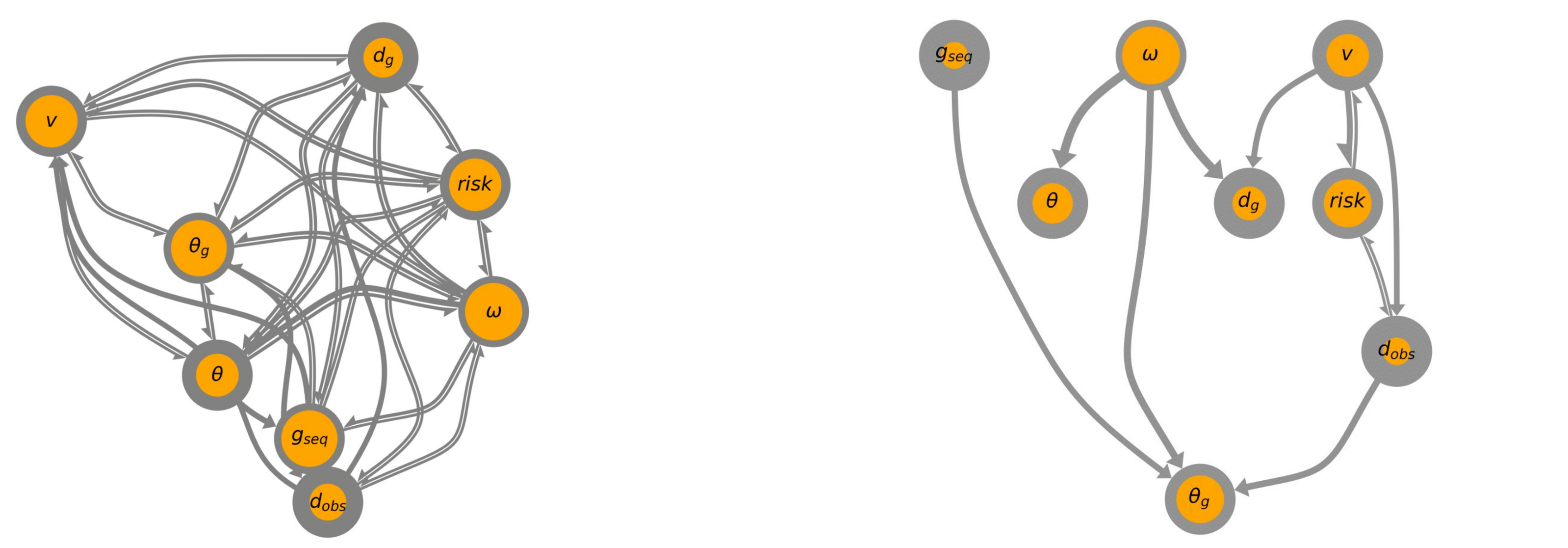
We used our approach to model and predict spatial interactions. This application involves three steps:



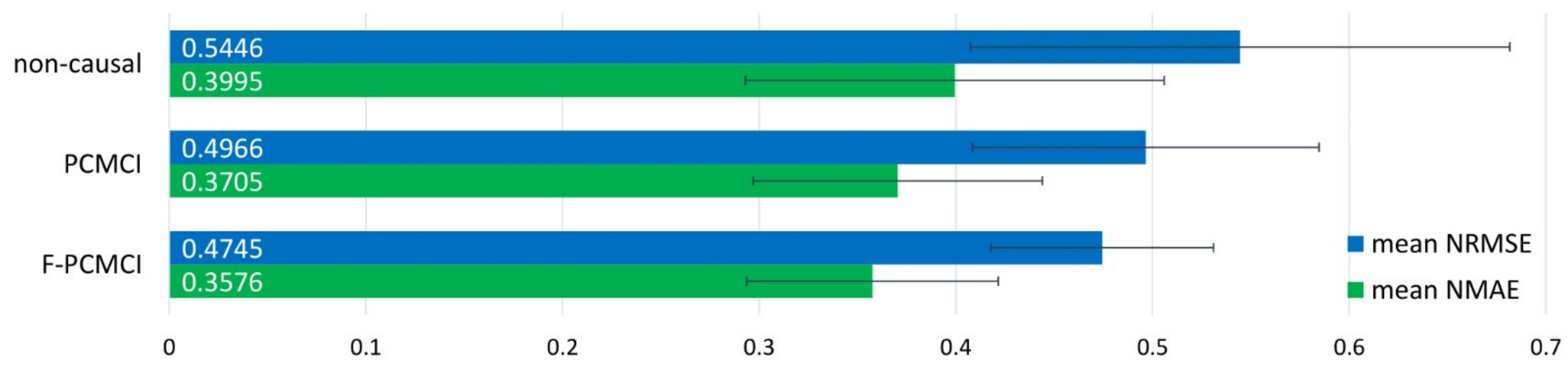
- extracting time-series of sensor data from human spatial interaction scenarios using the THÖR dataset [3];
- reconstruct the causal model using F-PCMCI;
- embedding the causal model in a LSTM-based prediction system inspired by [4].

In order to represent human spatial interactions, for each agent we considered 8 variables, which were then used in the causal analysis. These are the following:

d_g	- distance between the current position of the agent and its goal
v	- velocity of the selected agent
risk	- risk of collision with other agents, as proposed in [5]
θ	- orientation of the selected agent
θ_g	- angle between the current position and goal of the selected agent
ω	- angular velocity of the selected agent
g_{seq}	- sequence of goal positions reached by the selected agent
d_{obs}	- distance between the position of the selected agent and the closest obstacle



PCMCI execution time 79'45"	**F-PCMCI execution time 17'33"**



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This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017274