Discovering Causal Change Relationships Between Processes in Complex Systems

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Abstract—Complex systems involve the interaction between many processes that may or may not have causal relations to each other. In such systems, discovering causal relations can provide significant insights into the internals of the system and facilitate fault discovery and recovery procedures. In this paper, we provide a novel causality detection algorithm based on robust singular spectrum transform that combines features of autoregressive modeling and perturbation analysis. The proposed approach was evaluated using both synthetic and real data and was shown to provide superior performance to the standard linear Granger-causality test. It also provides a natural way to detect common causes that may give false positives in other causality tests.

I. INTRODUCTION

The study of causality can be traced back to Aristotle who defined four types of causal relations [1] (material, formal, efficient and final causes). From these four types, only efficient causality is still considered a form of causality today. In his Treatise of Human Nature (1739-1740), David Hume described causality in terms of regular succession. For Hume, causality is a regular succession of event-types: one thing invariably following another. In his words: We may define a CAUSE to be 'An object precedent and contiguous to another, and where all the objects resembling the former are placed in like relations of precedence and contiguity to those objects, that resemble the latter'. Since Hume, there were many definitions of causation [2]. There are two ingredient of the concept that are widely accepted by most definitions: causation is related to predictability from causes of effects and causation involves time asymmetry between causes and effects. Simply causes precede effects or at least cannot follow them in time. In fact this is the basis of the definition of Causal Linear Systems as used in electrical engineering literature.

There are three main definitions of causation that lead to computational models. Some theorists equated causality with increased predictability leading to Granger-causality tests [3] [4]. Some theorists have equated causality with manipulability [5]. Under these theories, x causes y just in case one can change x in order to change y. This is the root of causation from perturbation models [6]. Finally, yet other theorists define causality as a counterfactual which means that the statement ”x causes y” is equivalent to ”y would have happened if x”. This kind of definition of causality is the basis of Pearl’s formalization of the Structure Equation Model [7]. All of the three definition agree on the time asymmetry nature of causality.

There are two problems that most of these systems (taken alone) run into: causality cycles and common causes. Causality cycles (sometimes called feedbacks) happen when an event directly or indirectly causes itself to happen again in the future. Linear Granger causality can detect these cycles only if two independent null-hypothesis were rejected [8]. Common causes happen when event A causes both B and C but with different time delays. most techniques analyzing the behavior of B and C alone would result on the false conclusion that one of them is causing the other. When representing causality using graphs, causality cycles correspond to cycles in the graphs and common causes appear as bifurcations in these graphs [9].

A promising techniques for avoiding these problems is the causation from perturbation technique which is rooted in the work of the economist Kevin Hoover [6] who inferred the direction of causation among correlated economical variables (e.g. employment and money supply) by observing changes that sudden modifications of the economy (e.g. tax reformation) induce on the statistics of these variables. The main assumption was that the conditional probability of an effect given its causes should not vary due to economy modifications while the conditional probability of a cause given its effect can vary with such modifications. Formally, if E is an effect, C is its cause, \( P_a(x) \) is the probability distribution of \( x \) after the disturbance/modification of the generating process, \( P_b(x) \) is the probability distribution of \( x \) before the disturbance, and \( \Psi(P) \) is some statistic of \( P \), then:

\[
\Psi(P_a(E|C)) = \Psi(P_b(E|C)) \quad (1)
\]

\[
\Psi(P_a(C|E)) \neq \Psi(P_b(C|E)) \quad (2)
\]

This technique is usually used for confirming or rejecting specific causal models rather than discovering them from scratch.

In this paper, we combine elements from the predictability and manipulability approaches to overcome the problems of common causes and causal feedback. Moreover, our approach can discover the expected time delay between the cause and effect (assuming fixed context).

The rest of this paper is organized as follows: In section II we present the problem statement. In section III we introduce Granger-causality and its extensions and in section IV we show that traditional approaches to causality detection
including Granger-causality may not be able to capture the underlying causal structures in complex multidimensional systems. Section V details our RSST algorithm for change point detection that will be the basis of our causality detection approach then section VI shows how can RSST be extended to multiple dimensions. We then introduce our proposed causality detection algorithm in section VII, evaluate it in section VIII. The paper is then concluded.

II. PROBLEM STATEMENT

Given a set of $n_i$ timeseries of length $T$ characterizing the performance of $n$ processes (where $n_i \geq n$), build a $n$-nodes directed graph representing the causal relations between these processes. Each edge in the DAG should be labeled by the expected delay between events in the source processes and their causal reflection in the destination node.

We assume that every process $P_i$ generates a time series of dimension $n_i \geq 1$. This means that $n_i = \sum n_i$. Our goal is to build a graph that represents each process (not each time series) by a node and connects processes with causal relations using directed edge (cause as a source and effect as a destination). Each edge should be labeled by the expected delay time ($E(\tau)$) between a change in the cause processes and the resulting change in the effect process.

III. GRANGER-CAUSALITY AND ITS EXTENSIONS

There are many ways in which to implement a test of Granger causality. One particularly simple approach uses the autoregressive specification of a bivariate vector autoregression. First we assume a particular autoregressive lag length for every timeseries ($\rho_a, \rho_b$) and estimate the following unrestricted equation by ordinary least squares (OLS):

\[
\hat{A}(t) = \epsilon_1 + u(t) + \sum_{i=1}^{\rho_a} \alpha_i \hat{A}(t-i) + \sum_{i=1}^{\rho_b} \beta_i \hat{B}(t-i) \quad (3)
\]

Second, we estimate the following restricted equation also by OLS:

\[
\hat{A}(t) = \epsilon_2 + e(t) + \sum_{i=1}^{\rho_a} \lambda_i \hat{A}(t-i) \quad (4)
\]

We then calculate the sum of squared residuals (SSR) in both cases:

\[
SSR_1 = \sum_{i=1}^{T} e^2(t)
\]

\[
SSR_0 = \sum_{i=1}^{T} \epsilon^2(t) \quad (5)
\]

We then calculate the test statistic $S_{\rho_b}$ as:

\[
S_{\rho_b} = \frac{(SSR_0 - SSR_1)/\rho_b}{SSR_1/(T-2\rho_b-1)} \quad (6)
\]

If $S_{\rho_b}$ is larger than the specified critical value then reject the null hypothesis that $A$ does not granger cause $B$. The $p$-value in this case is $1 - F_{\rho_b,T-2\rho_b-1}(S_{\rho_b})$. As presented here Ganger Causality can be used to deduce causal relations between two variables assuming a linear regression model.

The test was extended to multiple variables and nonlinear relations (e.g. using radial basis functions) [10].

In [9], we utilized an extended version of the Granger-causality test combined with a constrained motif discovery (CMD) algorithm [11] to discover causal relations. The main problem with this approach is that a large amount of data is required in order for the CMD algorithm to discover meaningful recurrent patterns. Also CMD requires the specification of an upper limit on the motif length which may be difficult to give in some contexts.

Because the optimal lag is not usually known in advance, we use BIC (Bayesian Information Criteria) for selecting these lags in our evaluations.

IV. CHANGE CAUSALITY

The main insight of our approach is that causation can be defined as the predictability of change in the effect given a change in the cause rather than the predictability of the effect itself given the cause itself. Consider a differential drive robot navigating a 2D environment under gesture control from a user, concentrating the analysis on robot’s location and the rotation speeds of its two motors or even the hand motion of the user will reveal no causal relation at all because the position of the robot is actually not drivable from the commands given to it. The initial condition of the robot and environmental factors makes it very hard to predict its position from either motor speeds or user’s hand motion. It is not that these factors do not uniquely define the position, the main problem is that these factors do not even correlate with the position even though we can consider either of them the cause of the motion. In terms of g-causality the AR model induced using the position of the robot alone will not be less predictive than the AR model induced by adding the instantaneous value of either of these two factors. The fact that both motor speed and hand motion are multidimensional further complicates the problem as either dimension alone gives no information whatsoever about the next location of the robot even if we know the current position (except in the very special cases of zero or maximum motor speed). Fig. 1 shows the path of the robot, its horizontal ($x$), vertical ($y$), and orientation ($\theta$) state as well as the commands given to the robot.
left and right motors in radians/second. From the Figure, no clear causation can be inferred. Applying $g$-causality test as described in section III revealed no causality for AR models of orders 1 to 50 ($p_0$ in section III and corresponding to maximum delay before a change is propagated).

The main lesson of this example is that causation may not be readily inferred from predictability of the time series themselves. The concept of causation by perturbation comes here to rescue. If we can show that perturbing motor commands perturbs the behavior of the robot, then we may be able to infer the causality relationship. From this, we hypothesize that causation may be inferred not from the predictability of the timeseries themselves as in the standard Granger causality test but from the predictability of the change in them.

For this approach to work, we need a general change detection algorithm that can provide us with the ground-truth with which we compare our predictions. The following section introduces some of the approaches proposed in literature to solve this problem and describes in more details our Robust Singular Spectrum Transform (RSST) [12].

V. DETECTION OF CHANGE IN TIME SERIES DATA

Detection of change in time series is studied in data mining as the change-point discovery problem. Research in this area have resulted in many techniques including CUMSUM [13], wavelet analysis [14], inflection point search [15], autoregressive modeling [16], Discrete Cosine Transform, and Singular Spectrum Transform (SST) [17]. Most of these methods with the exception of SST either discover a single kind of change (e.g. CUMSUM discovers only mean shifts), require ad-hoc tuning for every time series (e.g. wavelet analysis), or assumes a restricted generation process (e.g. Gaussian mixtures). The main disadvantages of SST though are the sensitivity to noise and the need to specify five different parameters [12]. In this paper we use the Singular Spectrum based approach.

Singular Spectrum Analysis (SSA) is a technique for decomposing time series into a set of components that represent it. This decomposition can effectively separate the noise and signal in the time series [18], [19]. The algorithm was used for forecasting [20], change detection [21], [17] and many other applications [22].

In [12], we proposed the RSST algorithm which is based on SSA (and its change point detection version called SST [17]) but provides more resistance to noise and requires the specifications of less parameters.

The essence of the RSST transform is to find for every point $x(i)$ the difference between a representation of the dynamics of the few points before it (i.e. $x(i-p):x(i)$) and the few points after it (i.e. $x(i+g):x(i+f)$). This difference is normalized to have a value between zero and one and named $x_0(i)$.

The dynamics of the points before and after the current point are represented using the Hankel matrix which is calculated as:

$$H(t) = [seq(t-n),...,seq(t-1)]$$

where $seq(t) = \{x(t-w+1),...,x(t)\}$

Singular Value Decomposition (SVD) is then used to represent the genuine dynamics of the signal. To find a first guess of the change score around every point, RSST uses Eigen vectors of the Hankel matrix representing the future of the signal. RSST then keeps only the local maxima of change scores and normalizes the resulting time series by dividing with its maximum. Due to lack of space, details of RSST will be omitted from this paper. For the rationale behind RSST and example applications please refer to [12] and [11].

VI. DEALING WITH MULTIPLE DIMENSIONS

Algorithm 1 (Multidimensional RSST)

1: **Inputs**: $n,M_i(t) \ (1 \leq i \leq n)$
2: **Outputs**: $\hat{P}_i(t)$
3: **procedure** MRSSST
4: for $i \leftarrow 1 : n$ do
5: $\beta \leftarrow \text{Eigen vector with max. Eigen value of } M_iM_i^T$ (Eq. VI and VI)
6: $P_i \leftarrow \beta^TM_i$ (Eq. VI)
7: $\hat{P}_i \leftarrow \text{RSST} (P_i)$
8: end for
9: **end procedure

RSST works only on time series with a single dimension. Multidimensional SSA can be used as a basis for extending RSST to multiple dimensions [18]. In this paper we take a different route and convert the multidimensional time series corresponding to every process into a single dimensional time series. This way we can have a change score function corresponding to each process ($\hat{P}_i$).

Let’s assume that we have $n$ processes ($P_i$ where $1 \leq i \leq n$) each echoing $n_t$ synchronized time series (e.g. $x$, $y$ and $\theta$ in our navigation example). We utilize the assumption that the outputs of every process are independent of all other processes conditioned on the state of the process itself. Given this assumption we can process the $n_t$-dimensions time series echoed by each process ($P_i$) separately.

Assume that the number of timesteps is $T$, we can represent the output of the process $P_i$ as a $n_t \times T$ matrix $M_i$. Our goal is to convert $M_i$ into another $1 \times T$ matrix ($\hat{P}_i$) that best represent $M_i$.

To achieve that we find the Eigen values of the matrix $M_iM_i^T$ by solving:

$$M_iM_i^T\mu_j = u_j$$

for $1 \leq j \leq 3$

$$\beta = u_m$$

where $m = \arg\max_i (\mu_i)$
Now $\beta$ is a $n_i \times 1$ vector representing the Eigen vector corresponding to the largest Eigen value of $M_i M_i^T$. Finally we get the one dimensional time series $\hat{P}_i$ using:

$$\hat{P}_i = \beta^T M_i$$ (10)

Now we have a one-dimensional time series representing the state/output of every process. We can now use these signals for detecting any causality relationships between the generating processing as will be shown in section VII.

VII. PROPOSED ALGORITHM

In section III we introduced the traditional Granger-causality test then we showed in section IV that a better idea would be to base our causality assessment on the change of signals rather than the signals themselves. In section V we introduced our RSST algorithm for detecting changes in signals and showed how to extend it to multiple dimensions in section VI. With these pieces together we are ready to provide the proposed algorithm for causality assessment. The idea of using changes in signals to reveal information about the underlying dynamics was discussed in [23] but no quantitative causality test was given.

We apply Algorithm 1 to get the set of $\hat{P}_i$ processes representing the $n$ processes in the system and use these signals as the inputs of our algorithm.

Our main assumption is that if Process $i$ causes $j$ then $\hat{P}_i$ will most of the time if not always have major changes near $\tau_{ij}$ time-steps after $\hat{P}_i$ where $\tau_{ij}$ is a constant representing the delay of the causation. Because in the real world, many factors will affect the actual delay (add to this inaccuracies in the change point detection algorithm), we expect that in reality the delays between these change points will be well approximated with a Gaussian distribution with a mean of $\hat{\tau}_{ij}$ where $|\hat{\tau}_{ij} - \tau_{ij}| < \epsilon$ for some small value $\epsilon$. The main idea of our algorithm is to check for the normality of the delays and to use the normality statistic as a measure of causality between the two processes.

We start with a causality graph with $n$ nodes representing the processes and no edges. First, we scan all the $\hat{P}_i$ timeseries to find locations of change ($L_i$). This can be done in different ways. In this paper we simply find the midpoints of subsequences in $\hat{P}_i$ over some predefined threshold (we use 0.2 in all the experiments in our paper).

Second, for each pair of change point location vectors ($L_i$ and $L_j$ in order); we find the list of all delays between changes in processes $i$ and $j$ ($\{\tau_{ij}^k\}$). Notice that in general (if no causal loops exist) the sets $\{\tau_{ij}^k\}$ has nothing to do with $\{\tau_{ji}^k\}$. This is the reason that our graph will be directed.

To guard against inaccuracies in change point detection we remove from the set $\{\tau_{ij}^k\}$ all points that are more than 4 standard deviations from its median assuming that these points are outliers. Removal of outliers serves also to allow the system to work if the change caused by process $i$ in process $j$ happens with a probability less than one (but is still high enough to be detected). If it was expected that the causal changes are probabilistic then a different approach to this step would have been to cluster the delays and keep the cluster with largest number. This extension is behind the score of this paper.

Prior knowledge about the system can be incorporated at this stage. For example if we know that there can be no self-loops in the causality graph (a change in a process does not directly cause another change later) we can restrict the pairs of $L_i$, $L_j$ by having $i \neq j$. If we know that processes with higher index can never cause process with lower index, then we can restrict $i$ to be less than or equal to $j$. Extension to more complex constraints is fairly straightforward.

We then calculate a causality score from set $\{\tau_{ij}^k\}$ using its mean($\mu_{ij}$) and standard deviation ($\sigma_{ij}$) (after removing the outliers as explained before) by:

$$score = 1 - \exp\left(-\frac{\sigma_{ij}}{\mu_{ij}}\right)$$ (11)

This score is always between zero and one. The larger this score is, the more probable is it that there is a causal relation between processes $i$ and $j$. To construct the causality graph we accept the causal relation if this score was over some predefined threshold. In the causality graph we add an edge from $i$ to $j$ and associate with it the mean and variance of the delays ($\mu_{ij}, \sigma_{ij}$) calculated from $\{\tau_{ij}^k\}$. It is also possible to add to this edge’s label a confidence measure by dividing the number of times $L_j$ has a change after $\mu_{ij} \pm \delta$ from a change in $L_i$ to the number of changes of process $i$ ($|L_i|$. This confidence measure characterizes the predicting power of this causal relationship. We write this information as:

$$i \xrightarrow{\mu_{ij}, \sigma_{ij}, \epsilon_{ij}} j$$

After completing this operation for all $L_i$ and $L_j$ pairs (an $n^2$ order of operations), we have a directed graphs that represents the causal relationships between the series involved. The problem now is that this graph may have some redundancies. For example, Fig. 2(a) shows a redundant configuration. Here process 1 is causing changes in process 2 (with a delay 2.5 steps) which in turn is causing changes in process 3 (with a delay 4.3 steps) but this means that 1 is indirectly causing 3 with a delay of 6.8 steps. The extra arrow from 1 to 3 is redundant. In fact, there is an ambiguity here about which arrow is redundant because we can remove either $1 \rightarrow 3$ or $2 \rightarrow 3$. In this paper we resolve
this ambiguity by simply removing the causal relation with the longest time delay. A better approach would be keep multiple possible graphs and then use a causal hypothesis testing system like Hoover’s technique [6] for selecting one of them.

Not all closed loops of these form are in fact redundant. For example Fig. 2(b) shows a similar configuration. The only difference is that the delay associated with the causation arrow from 1 to 3 is now not equal to the sum of the other two delays. This means that process 1 directly causes changes in 3 and also indirectly causing other changes later through changing 2. The final step of our algorithm is to remove redundant edges similar to the one shown in Fig. 2(a). This is straightforward, and due to space limitations will not be detailed here.

We call this algorithm Delay Consistency-Discrete (DCD) because it requires a descetization of the MRSST output before it can be applied.

VIII. EVALUATION

We evaluated the proposed algorithm (section VII) using synthetic and real world data. This section reports supporting evidence that the proposed approach can indeed recover the causal structure of the system. To evaluate the effectiveness of the approach we need to compare the resulting graph to the true causal graph used to generate the data. In most (but certainly not all) real world situations we do not have access to this true causal graph. This is why we first evaluate the system on synthetic data.

Another problem is that we need a quantitative measure of the similarity of two causality graphs. We use the following measures: The Mathews Correlation Coefficient (MCC) distribution, the F-1 measure (F1), the root mean square difference in the delays (RMSD). A false positive will happen if an edge appears in the induced graph that is not in the true graph. A false negative will happen if an edge appears in the true graph that is not in the induced graph. A perfect detector will has one for the first two measures and zero for the last one.

A. Synthetic Data

First preliminary evaluation of the proposed algorithm was done using synthetic data that was generated using a deterministic model. The model consists of 15 signals \( X_1 : X_{15} \) each of which is a concatenation of the outputs from five different patterns (called models). These signals represent the state of a variable number of processes (4–8) with 1–6 dimensions each (to test MRSST).

The causality relationship was imposed by constructing a random causality graph with delays between 5 and 12 time steps and with a 2 points standard deviation of delay (not allowing self loops). This causality graph then selects the active model at every time-step of the effect signals given the active model in the cause signals. We generated 100 example graphs with a total of 847 causality links and used each of them to generate 8000-points timeseries. Gaussian noise with zero mean and unit variance was added to the data before processing. Fig. 3 shows an example short sequence of two example time series.

The proposed algorithm (section VII) and the standard Granger causality test (section III) applied to both the signal directly and the change scores found by RSST where applied to the data. For comparison we also applied the Granger causality test and the proposed algorithm using the optimal locations of changes in the signal to measure the asymptotic behavior of our approach for more accurate change detectors. Fig. 4 shows the results of this experiment for one example causality graph. As the Figure shows, with optimal change detection the proposed approach was able to recover the exact underlying causal structure while g-causality failed even with this optimal detector. Using the more realistic RSST change detector, DCD was able to recover most of the causal structure with some false positives and negatives corresponding to an F-measure value of 0.741. Fig. 5 show the distribution of MCC and F1 measures for the five algorithms. Using an optimal change detector was able to improve the performance of both the Granger-causality test and DCD. The difference is statistically significant in both cases. Using MRSST for change point detection did not improve the performance of the Granger-causality test over applying it directly to the signals but was able to improve the performance of DCD to
Fig. 5. The F-1 and MCC measures for the five tested algorithms on synthetic data.

Fig. 6. Execution time per point for the five algorithms.

Fig. 7. The experiment setup. The actor is a WOZ operated robot. Command stream is 48 dimensions accelerometer and position sensor signals, and the action stream is 6 dimensional absolute and operator-relative location of the robot.

achieve the same performance of the Granger-causality test on the optimal change detector. MRSD was zero for DCD with the optimal detector (which is expected) and was 2.314 for the more realistic DCD+MRSST algorithm. This shows that the delays attached with the detected causality relations were acceptably close to the real delays used for generating them.

Fig. 6 shows the execution time for the five algorithms tested in this paper. The proposed DCD algorithm combined with MRSST requires around 18 $\mu$s per point while the standard linear Granger-causality test will require alone around 11 $\mu$s which is a difference more than justified by the improvement in MCC and F1. Another point that is not clear from Fig. 6 is that the Granger-causality test’s will slow down with increased lag between processes while the proposed approach will not be affected by such increased lag.

These results though are to be taken with caution because the process of time-series generation was somehow tuned for the use of our algorithm. To show that the performance of the proposed algorithm is still robust enough with real world data, we tested it in a robot guided navigation task.

B. Robot Guided Navigation

This section presents a feasibility study to assess the applicability of the proposed approach in learning the causal structure in a controlled experiment. This task was selected because it has a known causal structure that we can compare quantitatively to the results of applying our proposed algorithm.

The evaluation experiment was designed as a Wizard of Ooz (WOZ) experiment in which an untrained novice human operator is asked to use hand gestures to guide the robot shown in Fig. 7 along the two paths in two consecutive sessions. The subject is told that the robot is autonomous and can understand any gesture (s)he will do. A hidden human operator was sitting behind a magic mirror and was translating the gestures of the operator into the basic primitive actions of the WOZ robot that were decided based on an earlier study of the gestures used during navigation guidance [24], [25].

In this design the movement of the robot is known to be caused by the commands sent by the WOZ operator which in turn is partially caused by the gestures of the participant. This can be formally explained as:

$$G_{i} \xrightarrow{T_{g} \times 0.1} W_{j} \xrightarrow{T_{w} \times 0.1} M_{k}$$

where $G_{i}$ represent some gesture done by the participant, $W_{j}$ represent some action done by the WOZ operator (e.g. pressing a button on the GUI of the control software), and $M_{k}$ represents some pattern in the movement of the robot (e.g. moving toward the participant, stopping, etc).

The total number of sessions conducted was 16 sessions with durations ranging from 5:34 minutes to 16:53 minutes. The motion of the subject’s hands ($G$) was measured by six B-Pack ([26]) sensors attached to both hands as shown in Fig. 7 generating 18 channels of data. The PhaseSpace
motion capture system ([27]) was also used to capture the location and direction of the robot using eight infrared markers. The location and direction of the subject was also captured by the motion capture system using six markers attached to the head of the subject (three on the forehead and three on the back). 8 more motion capture markers were attached to the thumb and index of the right hand of the operator.

The following four feature channels were used as representation of robot’s action ($M$):

- The directional speed of the robot in the XZ (horizontal) plane in the direction the robot is facing (by its cameras) (2 dimensions).
- The direction of the robot in the XZ plane as measured by the angle it makes with the X axis (1 dimension).
- The relative angle between the robot and the actor (1 dimension).
- The distance between the operator and the actor (1 dimension).

The time of button presses in the GUI used by the WOZ operator was collected in synchrony with both participant gestures and robot actions. The interface had seven buttons (related to robot motion) each of which can be toggled on and off and a single button can be on at any point of time. The WOZ operator’s actions were represented by a single input dimension giving the ID of the currently active button (from 1 to 7).

This leads to a total of 67 input dimensions. The generating causal model (ground truth) consists of seven gestures, seven button press configuration and corresponding seven robot actions (21 total patterns). Fig. 8 shows two example gestures.

There are four processes in this system representing the user, the operator, the motors of the robot, and the configuration of the robot (location/orientation). The causal structure of this problem as set by the controlled experiment setup is very simple $user \rightarrow operator \rightarrow robot_{motors} \rightarrow robot_{configuration}$. The true value of the delays are not controlled in the experiment and for this reason we cannot measure RMSC for this problem.

We applied the algorithm first to the collection of all interactions and it was able to discover the exact causal structure of the problem with any threshold value larger than 0.1. This shows that our proposed approach can solve the example navigation problem we mentioned in section IV.

We also applied the algorithm to each interaction alone and calculated the number of times each causal relation was discovered correctly. The relation $user \rightarrow operator$ was found 83.4% of the time and the relation $operator \rightarrow robot$ was discovered 91.6% of the time. The system had two single false positives in two sessions and both where $robot \rightarrow operator$. In fact these errors can be explained because the hidden operator in our experiment had some hard time dealing with rotation commands and repeatedly did the wrong rotation then he had to correct it which appeared as if these corrections are caused by robot’s behavior. These results show that the proposed algorithm can successfully discover the causal structure of this real world experiment with known causal structure.

IX. CONCLUSIONS

This paper presents a novel causality detection algorithm that can learn causality graphs from the behavior of multiple processes in a complex system. The proposed algorithm combines SSA based change detection, PCA projection for dimensionality reduction and a novel delay consistency test to detect causal relations in process changes. The proposed approach can also discover the statistics of the delay between the change in the cause and its effect and can assign a confidence level to each of the relations it discovers. The proposed algorithm was evaluated using both synthetic data and data from a real world gesture guided robot navigation experiment and was shown to recover the underlying causal structure accurately while traditional Granger causality tests failed to discover any useful causal relations in the data. In the future we would like to extend the proposed approach to the case when the delay between the cause and effect is not normally distributed (or even unimodal) using mixtures of Gaussians to model the delay. The proposed approach will also be applied to evaluate the relation between psychophysiological signals and EEG readings of human partners and their behavior during face to face interactions.

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