A Dependency Detection Method for Sensor-based Fault Detection

Pooja Bhat, Santosh Thoduka and Paul G. Plöger
Hochschule Bonn-Rhein-Sieg, Sankt Augustin, Germany
e-mail: pooja.bhat@mail.inf.h-brs.de, <santosh.thoduka, paul.ploeger>@h-brs.de

Abstract

In Sensor-based Fault Detection and Diagnosis (SFDD) methods, spatial and temporal dependencies among the sensor signals can be modeled to detect faults in the sensors, if the defined dependencies change over time. In this work, we model Granger causal relationships between pairs of sensor data streams to detect changes in their dependencies. We compare the method on simulated signals with the Pearson correlation, and show that the method elegantly handles noise and lags in the signals and provides appreciable dependency detection. We further evaluate the method using sensor data from a mobile robot by injecting both internal and external faults during operation of the robot. The results show that the method is able to detect changes in the system when faults are injected, but is also prone to detecting false positives. This suggests that this method can be used as a weak detection of faults, but other methods, such as the use of a structural model, are required to reliably detect and diagnose faults.

1 Introduction

The development of fault detection and diagnosis (FDD) methods is critical to ensure safety and reliability of autonomous systems. The complexity of the systems and high interaction with operating environment make them highly susceptible to faults. The faults associated with these complex systems vary highly and it is implausible to foresee every fault during the system design stage. To provide quick detection, faulty execution models can be used, but unforeseen faults remain undetected [1]. The Sensor-based Fault Detection and Diagnosis (SFDD) approach, which is the focus of our work, does not require any a priori information; instead it exploits the spatial and temporal dependencies among the sensor data streams to further use them for fault detection [2][3][4].

An autonomous system acts as an agent that maps between perception and actuation. It operates iteratively in a general pattern of sensing the environment through sensors, which creates beliefs about its surroundings, based on which it executes several commands with the help of various software and hardware components. When any subsystem has a fault, the reliability of the system degrades, increasing the likelihood that a task cannot be accomplished. For example, an ultrasonic sensor used for object detection induces a belief in the system about the distance of an object from itself with each reading. If this detected object is a target object and if the system is given an incorrect value, the task to reach the target remains unaccomplished. Thus, sensors play a vital role in the maintenance of system health. Faults occurring in sensors or actuators have to be detected and diagnosed, especially in harsh environments, to prevent task failure. The detection of faults at the lowest level would allow the opportunity to recover before the fault is propagated to the execution level.

In [2], a structural model that infers the dependency of sensors on other components was proposed with a hypothesis that if a given component is faulty, then the fault is propagated to all of its dependent sensors and actuators. The detection of correlated or dependent sensors is an important step because it indicates that, during nominal operation, they exhibit similar behaviour. If this dependency is violated, it is an indication of a fault. In particular, in their work, they describe two methods; one which performs online correlation detection and one offline. The Pearson correlation coefficient is used to find sensor streams which are temporally correlated in the first half of a sliding window. In the second half of the window, if correlated streams display different patterns, a fault alarm is raised. To be specific, at every instant (in a window of predetermined size), when the sensors that are expected to hold a functional relationship, violate their dependency, the sensor that exhibits a suspicious pattern (such as drift/stuck) is considered to be faulty. When a fault is found, this can be extended to higher levels. For example, when multiple sensors depending on the same component exhibit faulty behaviour, the hypothesis states that the component is faulty. The system elements are tested at each level until the faulty sensor/component/system is detected. One drawback is that Pearson correlation does not work well in the presence of noise and also fails in certain corner cases, for example, with a zero signal. Additionally, as stated in [2], there is a need to set a threshold for the correlation coefficient for the selection of correlated sensor pairs. A high threshold of 0.9 is suggested, such that only highly correlated sensors are considered.

In this work, we propose the use of Granger causality, a statistical hypothesis test, as an alternate approach to model dependencies between sensor data streams. Granger causality has been used previously for fault detection in sensor networks[5], where both spatial and temporal dependencies between pairs of data streams are modelled based on their Granger-causal relationship. Given two time series (for example, sensor stream X and sensor stream Y), the Granger
causality test indicates whether the past values of $Y$ leads to a better prediction of future values of $X$ than when using the past values of $X$ alone. Here, we use the Granger causality test to find pairs of sensor variables which are Granger causal during nominal operation and indicate a fault if they are no longer causal. In addition to testing the ability of the method to detect the injected internal fault in the system, the experiment is also extended to examine the behaviour of the method on external faults / exogenous events. This provides for a detailed analysis of the performance of the method in various frequently occurring real time abnormalities that are hard to detect.

2 Related Work

Identification of faults in sensors, referred to as sensor validation is a widely used approach in the field of fault detection and diagnosis [6]. The approach exploits the data from sensors and validates in two broad ways, either from a single sensor or from a set of sensor data streams. When single sensor data is considered to identify faults, the health information of the sensor is often provided by limit filtering or specifically, limit checking with a defined threshold [7]. The methods that exploit data from a set of sensors use the redundant information from the sensors, and are based on the principles of physical or analytical redundancy [3].

In a system, physical redundancy of sensors exists due to more than one sensor measuring the same parameter. In [8], drift of the sensor is corrected by detecting and accommodating intermittent and soft sensor faults with fuzzy principles using physical redundancy in the system. This involves inspection of differences existing among redundant sensors. Widely used analytical redundancy on the other hand assumes that a normal execution model is available and tend to use the functional relationships existing among sensors. Here, the residual is obtained by comparing actual output with the nominal model. One of the most popular analytical approaches is the Multiple Model Adaptive Estimation (MMAE) approach [9]. This approach is used in [10] for parallel prediction of outcome of several faults and to detect faults in wheeled mobile robots. For each type of fault, the system behavior is modeled and the models are embedded in several Kalman filters which are used as parallel estimators set to particular fault. The estimation of the sensor readings provided by the estimators are used to generate residuals from which faults are detected. This method applied to the case of mechanical failures were extended for 'hard' and 'soft' sensor failures in [11].

Although analytical/model-based techniques rely on a mathematical model describing the system to provide appreciable results and do not require redundancy in a system, the assumption of the existence of a perfect mathematical model of the system limits the performance [12], as the physical reality is beyond the reach of the model. Hence in [13], a model free, sensor based approach is introduced to detect anomalies in unmanned vehicles. The sensor readings form a cluster of observations and when every new observation/vector is provided by the sensor, it is compared with clusters using Mahalanobis distance.

In [2], Sensor-based Fault Detection and Diagnosis (SFDD) method used supervised structural model approach. This combined model-based approach with data driven approach to exploit advantages of both the methods. The dependencies between the sensor signals are detected using Pearson correlation coefficient with an estimated threshold to further apply it for sensor-based fault detection and diagnosis. In [14], the SFDD method is further extended and is shown to be satisfying the requirements of robotics systems as it is significantly accurate, quick, computationally inexpensive and can be implemented online. It is also able to detect unknown faults and is practical to construct.

Correlation being an intuitive way of detecting dependencies, is a popular dependency detection method. In a system, various sensors exhibit spatial and temporal correlation. While temporal correlation exists due to the effect of sensor readings observed at time $t$ on the observation at time $t + 1$, spatial correlations occur due to identical readings of the sensors located at small distance from each other [15]. In [4] where quasi-redundant sensors are used to increase confidence in the measurement, correlated and not necessarily redundant sensors are used. In [16], a metric-correlation-based-distributed fault detection (MCDDF) is proposed for wireless sensor networks to detect faults when correlation between sensor nodes’ system metrics that behaves normally in nominal state turns abnormal. In [17], recursive least squares method models the relationship between correlated input-output pairs online and uses the model to detect abnormalities in an aircraft. However, correlation assumes observations to be conditionally independent and computation of correlation is expensive especially in the case of distributed detection system [18]. Although from literature it is clear that correlation (including cross-correlation) is widely used in sensor dependency detection, the method is highly sensitive to noise and user-defined threshold [5].

The Granger causality test is used in [5] to model functional relationships among sensors, with an intent to overcome the demerits of cross-correlation. Granger causal dependencies are defined to represent spatial and temporal relationships among multiple sensors and the dependency graph proposed in [3] is extended reducing sensitivity to noise and eliminating the need for user-defined threshold. This also provides a unique approach in terms of directionality as the dependencies between sensors are directed. It is stated in [5] that Granger causality is applied in various economic and medical applications, but, it has been applied for fault detection and diagnosis application for the first time in the literature.

In this work, we propose Granger causality test method for sensor dependency detection for structural model framework as proposed in [2] to overcome the shortcomings of correlation. We also show that the method is robust to noise and lag as compared to correlation.

3 Approach

Sensor dependencies in a system occur due to various reasons. In this work, the dependency that exists due to the influence of one variable on the other variable is exploited. This is achieved by using causal dependencies, as proposed by Clive Granger in [19].

3.1 Definition

Granger causality is a statistical test to determine the Granger causal relationship between time series. According to this, if the past values of time series $Y$ can provide better prediction of another time series $X$ than past values of $X$ alone, then, $Y$ Granger-causes $X$. 
The definition of Granger causality can be explained using simple vector autoregression model. Consider the following equations,

\[ X(t) = a_0 + a_1 x_{t-1} + a_2 x_{t-2} \ldots + a_p x_{t-p} + \epsilon_{t+1} \quad (1) \]

\[ X^*(t) = a_0 + a_1 x_{t-1} \ldots + a_p x_{t-p} + b_1 y_{t-1} \ldots + b_p y_{t-p} + \epsilon_{t+2} \quad (2) \]

Eq.(1) and Eq.(2) form a model with two variables \( X \) and \( Y \), \( (n=2) \). The model represents the evolution of \( n \) variables over time \( t = (1, 2, \ldots, T) \). \( a_0 \) is a vector of intercepts, \( t-p \) refers to \( p \)th lag of the variable, \( a_i \) and \( b_i \) \( i = (1, 2, \ldots, p) \) are time-invariants and \( \epsilon_t \) are the error terms with mean zero.

### 3.2 Modelling Dependency between Two Data Streams

Eq.(1) is referred to as the restricted model where \( X \) is dependent only on its past values whereas Eq.(2) is referred to as the unrestricted model where \( X \) depends on past values of \( Y \) in addition to its own past values. A statistical test \( (t\text{-test/F-test}) \) can be applied to test the following null and alternate hypotheses:

\[ \begin{align*}
H_0 : \ b_i & = 0 \text{ for } i \in [1,p] \quad \text{(null hypothesis)} \\
H_1 : \ b_i & \neq 0 \text{ for at least 1 of } i \in [1,p] \quad \text{(alternate hypothesis)}
\end{align*} \]

The null hypothesis \( H_0 \) is accepted when Eq.(2) does not provide a better prediction than Eq.(1) for future values of \( X \). If not, the null hypothesis is rejected and the alternate hypothesis \( H_1 \) is accepted, indicating \( Y \) Granger causes \( X \).

To apply a statistical test, the dependent variable is regressed on its past values using the least squares method. This is called restricted regression and from this, the restricted sum of squared residuals is obtained. Further, the regression is computed using the unrestricted model that includes both dependent and independent variable in order to obtain the unrestricted sum of squared residuals. These residuals of both the models are compared to obtain F-value. If the F-value is greater than F-critical, then the null hypothesis is rejected [20].

The F-value is given as,

\[ F = \frac{SSR_u - SSR_r}{p \times SSR_r \frac{1}{T-2p-1}} \quad (3) \]

where \( SSR_r \) and \( SSR_u \) are the sum of squared residuals from the restricted and unrestricted models respectively; the number of observations along with the lag value \( p \) form the degrees of freedom \( T \).

If \( SSR_u < SSR_r \), this indicates that the unrestricted model provides a better prediction than the restricted model. Correspondingly, the F-value would be high, hence rejecting the null hypothesis and stating that \( Y \) Granger-causes \( X \).

Algorithm 1 describes the proposed method for dependency detection between two sensors. In the implementation, p-values corresponding to F-values (inversely proportional) obtained from F-test are used and the null hypothesis is rejected if p-value < 0.05. The p-value of 0.05 is universally accepted threshold for Granger causality. The maximum lag is set to be approximately equal to one third of the size of the dataset.

#### Algorithm 1: Granger causality based dependency detection algorithm for a pair of variables

**Input**: Dataset \( Z_N = \{ X(t), Y(t) \}_{t=1}^N \), maxlag \( p \), threshold value \( F_{crit} \)

**Output**: Dependent variables \( D = \{ \} \)

1. Set an empty list \( F = \{ F_1, F_2, \ldots, F_p \} \)
2. for \( lag \in \{1, \ldots, p\} \) do
3. Fit the VAR model in Eq.(1) and Eq.(2) from data \( Z_N \) to obtain \( SSR_u \) and \( SSR_r \); 
4. Compute \( F_{log} = \frac{SSR_u - SSR_r}{p \times SSR_r \frac{1}{T-2p-1}} \)
5. end for
6. Find \( F_{max} = \max(F) \)
7. if \( F_{max} \geq F_{crit} \) then
8. \( D \leftarrow D \cup \{X(t), Y(t)\} \)
9. end if

### 4 Comparison of Granger Causality with Correlation on Simulated Signals

To analyse the performance of the proposed Granger causality method, it is compared with Pearson correlation coefficient on simulated signals with lag and noise. The simulated signals here are sine waves with varying frequencies, amplitudes and random noise; we expect these signals to be correlated and have a Granger-causal relationship. The p-value of Granger causality ranges from 0 to 1, where p-value \( \leq 0.05 \) denotes high dependency between the signals and \( p \)-value >0.05 denotes less likelihood of dependency. The Pearson correlation coefficient varies between -1 to 1 with -1 denoting negative correlation, 1 denoting positive correlation and 0 denoting no correlation.

#### 4.1 Performance on Signals with Lag

As Granger causality claims to find dependencies on lag-lead relationship, it is important to assess the effect of lag in the signals on Granger causality.

![Signals with different lags](image)

(a) Signals with different lags.

![Signals to be dependent](image)

(b) Signals to be dependent on.

Figure 1: Sine waves considered to analyze dependency.

![Granger causality](image)

(a) Granger causality

![Correlation](image)

(b) Correlation

Figure 2: Performance on signals with lag

In this case, the dependencies of sine waves with some lags shown in Fig.(1a) on the sine waves with different am-
amplitudes (1 and 0.5) shown in Fig.(1b) are tested using both methods. In the considered sine waves, with the increase in lag, crests and troughs partially overlap. This may confuse dependency detection methods. The results from both methods for considered dependencies with high amplitude signal from Fig.(1b) are shown in Fig.(2).

From the results, it can be observed that p-value is consistent and accurately detects the dependencies as shown in Fig.(2a). As the correlation coefficient drops steeply from 0.75 to -0.5 as shown in Fig.(2b), it fails to draw any appropriate conclusion. The result remains identical for low amplitude signal in Fig.(1b) (hence, results not shown here), indicating that amplitude has no effect in the case.

4.2 Performance on Signals with Noise

In this case, analysis is carried out to test performance of the methods in the presence of noise, on sinusoidal signals with different amplitudes. Fig.(3a) and Fig.(3b) show sine waves with different amplitudes with some randomly distributed noise. The signals from Fig.(3a) are expected to show dependency on the signals from Fig.(3b), which has comparatively has more noise. Fig.(3a) includes signals with very low amplitudes (amplitude of 0.05, 0.3), which with noise appear to be flat signals with noise. Dependencies of these signals can be difficult to detect.

The results of both methods with dependencies of signals in Fig.(3a) with low amplitude signal of Fig.(3b) are shown in Fig.(4). The p-value is slightly above zero (around 0.02) when signal with very low amplitude (amplitude = 0.05) is considered to detect dependency as shown in Fig.(4a). The curve of p-value is above zero (around 0.04), when high amplitude signal (amplitude = 2.0) is compared against the comparatively low amplitude signal (amplitude = 0.5). Pearson correlation coefficient value is very low for low amplitude (0.05) as shown in Fig.(4b).

5 Experimental Evaluation

We evaluate the feasibility of using Granger causality for fault detection by using sensor data from an autonomous mobile robot. The use cases include internal faults, such as disconnected cables, and external faults, such as blocked wheels.

5.1 Experimental Setup

The ropod (figure 5a) is an Automatically Guided Vehicle (AGV) for logistic applications developed as a part of the ROPOD project. It consists of four smart wheels (SWh) which each provide more than 30 internal state variables including sensor readings and possesses a strict modular structure. This makes it suitable for decomposition of the system into a structural model, providing a natural hardware framework for the dependency detection problem, that aims to satisfy structural model-based approach for fault detection.

![The ropod platform](http://ropod.org/preliminary_results.html)

Each SWh, comprising of twin-wheels in a differential drive configuration with a castor offset (Fig.(5b)), can be viewed as an individual system consisting of various sensors and actuators. While data was collected for the all four smart wheels the proposed solution can be applied at wheel subsystem level as well.

Both wheels in the unit have in-wheel 3-phase brushless DC motors and an encoder. The encoders are used to obtain the absolute position of the twin-wheels. In addition, a pivot encoder is positioned to measure orientation of the SWh unit. An on-board IMU sensor, temperature sensor and pressure sensor are also present on the SWh controller board.

In addition to the main sensors (i.e three encoders, IMU, temperature and pressure sensor), there are current and voltage variables that are sensed internally, and their values can be accessed. Derived variables (such as encoder velocity) are also available. Commands are sent to the smart wheel as current set points (in amps) for each wheel.
5.2 Tests and Results

The experiment is conducted by introducing various abnormalities in the system. These considered cases are classified into internal faults, external faults / anomalies.

Use-cases and Dataset

The data collected for the experiment is generated by introducing some internal/external faults in to the ropod platform. The internal faults refer to the deviation from the expected behaviour of at least one of the components of the system, which prevents task execution. On the other hand, external faults or exogenous events are not the fault of system itself, but frequently occur due to dynamic nature of the environment [21]. These faults are usually unpredictable.

In this experiment, internal faults are introduced by:

- disconnecting the power supply to one of the wheels in a SWh unit
- disconnecting an encoder cable

The external faults are introduced in the experiment by:

- inducing wheel slippage to one of the SWh units
- blocking one of the wheel units with a wedge while the robot is in motion

Results

Fig.(6) shows a heatmap indicating the Granger causal relationship between all pairs of variables during nominal operation of the ropod. The shade of each box depicts the range of p-value, with lightest being p-value 0, denoting high Granger causal relation and darkest region indicates p-value 1 with no relation. The causal direction is from the x-axis to the y-axis (i.e variables in x-axis Granger cause those in y-axis). The dark diagonal elements exhibit the principle of Granger causality, as the diagonal p-values indicate the Granger causal relation of variables with themselves. As expected, a variable does not Granger-cause itself, since in Eq.(3), the residuals from both the restricted and unrestricted models would be identical.

In Fig.(7a), we observe that when the power cable to the second wheel of a SWh unit is disconnected, the Granger-causal relationship for the current variables for that wheel \(current_2 (u/v/w/d/q^2)\) changes compared to the nominal case. They no longer have Granger-causal relationships with most other variables. Similarly, in Fig.(7b), disconnecting the encoder cable of the first wheel results in a change in the causal relationship of the variables \(encoder_1\) and \(velocity_1\). In Fig.(7c), there are no significant changes in the relationships, and in Fig.(7d), several variables indicate a change, including \(encoder_1\), \(encoder_2\) and \(encoder_pivot\).

With the exception of the wheel slippage case, the variables associated with the fault show a change in their Granger-causal relationships with the other variables compared to the nominal case. For example, in the blocked wheel case, it can be argued that when a current is applied to the motors, in the nominal case, encoder values increase, whereas in the faulty condition the applied current does not induce a change in the encoder values; hence there is no longer a causal relationship.

Figure 6: Heatmap showing p-values for the Granger causality test for all pairs of variables. Darker shades indicate a higher p-value meaning a variable on the x-axis does not Granger cause the corresponding variable on the y-axis.

(a) Disconnected power cable (b) Disconnected encoder cable
(c) Wheel slip (d) Blocked wheel

So far we have only considered the nominal and faulty states separately. However, a robot must be able to detect a change in the causal relationship among variables during runtime. In particular, this implies keeping track of Granger-causal variables and detecting when they are no longer causal, while accounting for false alarms. This also brings in additional parameters, such as the window size, which would affect how well the relationships are captured and the delay in detecting a fault.

To observe the behaviour of dependency detection method in a real time scenario, a pair of sensor signals from

\[ u/v/w \]

is directly sensed 3-phase current and \( q, d \) are quadrature current and direct current derived from 3-phase current respectively.
nominal execution are considered on a sliding window of a defined size, and faulty data from fault injected execution is concatenated with one of the signals to simulate the occurrence of a fault during runtime. A phase current variable from a nominal and a faulty smart wheel units from the same trial is considered to observe change in the behaviour of p-values with the injection of fault. Here we also plot the Pearson correlation coefficient for comparison.

The behaviour of p-values and correlation coefficients can be observed in the Fig.(8); both increase after the fault event indicated by the blue dotted line. While the p-value remains close to zero in first half of the window, the Pearson correlation coefficient is around -0.5. The dependency of the two sensors defined by correlation for this region hence strongly depends on the user-defined threshold. Before the injection of the fault, the p-value rises above the threshold several times, which, without further processing would result in false alarms. After the fault is injected, both values rise after a short delay. The delay in both cases is due to the size of the window used. In this case, both Granger causality and the Pearson correlation coefficient are relatively good indicators of a fault. The experimental results show that Granger causality is capable of detecting dependencies in real time, considering the raw sensor data is used in the experiment. The existence of Granger causal dependencies is not consistent as p-values vary in each considered case unlike correlation. Though the method is comparatively slower than correlation, it certainly overcomes the demerits of correlation such as sensitivity to noise and user-defined threshold.

6 Conclusions

In this work, a statistical framework, Granger causality, is proposed as an alternate method to correlation for dependency detection among sensor streams. The performance of the method is compared with correlation method on some simulated signals, showing that Granger causality is better at detecting dependencies especially in presence of noise and lag in the signals. Experiments are also conducted on the robot platform, to detect the violation of previously existing dependencies when faults are injected.

The results from the method shows that the dependencies detected by Granger causality are less intuitive as compared to correlation. In other words, the correlation relationship between two signals is predictable based on the behaviour (for example, when the signal values increase or decrease together). However, Granger causality between signals is not easy to predict. It does not exploit redundant information from the system like any typical dependency detection method but instead checks the ability of one signal to predict the future values of the other. However, this overcomes a shortcoming of correlation, reliance on redundancy, as mentioned in [2].

The method is robust to noise and lag and outperforms correlation method when data has considerable lag and noise as shown in section 4. The method is capable of exploiting spatial and temporal dependencies and works well in various cases, showing promise for successful integration with the structural model framework. However, the method is comparatively slower than correlation which makes it less suitable for online dependency detection. Also, the small peaks in Fig.(8) show that the method is susceptible to false alarms, suggesting that additional reasoning (such as with a structural model) is required to make it a viable method for fault detection.

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References


