A Simplified Framework for Fault Prediction in Radar Transmitter based on Vector Autoregression Model

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Abstract

The prediction of faults in radar subsystems remains a challenge. It is common practice to use multiple sensors to monitor the performance of electronic components in radar. The complexity of processing the measurements increases with the number of monitored quantities. In this paper, we presented a simple method to predict the fault degradation of radar transmitter. Using historical data of monitored quantities leading to two different faults, the vector autoregression model is applied to predict future values of monitored quantities resulting in fault degradation in marine radar. The results showed that the proposed method can be useful for cases where failure in subsystem needs to be promptly detected and corrected to avoid overall system failure. We also demonstrated the performance of the proposed method on interpolated data generated from radar transmitter fault data.

1. Introduction

The advancement of radar technology has led to its extensive use in a wide range of applications, including defense systems in military, collision avoidance systems in automotive industry, and navigation systems in marine industry, etc. Considering the importance of radar in these areas, the reliable and accurate operation of radar systems is essential for achieving the various intended functions. However, when faults occur in radar systems, these can lead to reduced performance, increased downtime for repairs, and potentially dangerous situations. As such, the prompt detection and diagnosis of faults in radar systems is critical for maintaining safety and reliability. Fault monitoring systems, such as built-in self-tests, fault detection, and isolation algorithms, can identify and diagnose faults in radar systems but the fault data obtained from the radar transmitter is small and unbalanced for predicting faults in radar transmitter.

Appreciable attempts from different authors to estimate fault degradation of marine radar transmitter had been reported. Zhai and Fang (2020) installed 8 sensors to monitor faults in the transmitter of marine radar. The monitored data were preprocessed to remove noise using the wavelet threshold denoising technique. With long short-term memory (LSTM) neural network architecture, future values of the monitored data were predicted. The monitored quantities that deviated significantly from the expected distribution were compared using the multivariate Gaussian distribution model. The deviated quantities revealed the performance degradation of the radar transmitter. Building on this study, Zhai, Shao, Li, and Fang (2021) applied the isolation forest model to report early warning of fault in the marine radar transmitter. The unsupervised machine learning model is scalable, efficient, insensitive to multidimensional outliers, and does not rely on assumptions of the distribution of the monitored quantities.

In a more recent study, Zhai, Liu, Cheng, and Fang (2022) extended the prognostic model in Zhai et al. (2021) by using a multivariate isolation forest to determine the performance degradation of the radar transmitter. In addition, a modified auto-regressive integrated moving average (DU-ARIMA) with the capability to dynamically update itself, was used to predict future values of the monitored quantities before applying the multivariate isolation forest. Although, the root mean square error (RMSE) of the method in Zhai et al. (2022) is less than the LSTM-based method in Zhai and Fang (2020), the superior performance may not be guaranteed when the data is large. Secondly, the prediction of the future values of the monitored quantities using univariate prediction model (DU-ARIMA) did not explore the interdependencies between the monitored quantities.

To address these limitations, this paper presents a simple framework to predict faults in radar transmitter using the vector autoregression (VAR) model. The model takes advantage of the interdependency of the multivariate time series data of interpolated fault data to predict future values. Interpolation method based on piecewise cubic hermite interpolating polynomial (PCHIP) method is performed on the fault data to increase sample size. The proposed fault prediction method is described in section 2. The experimental results are discussed in section 3 and the conclusion in section 4.

2. Fault Prediction Model

This section describes the proposed fault prediction model. The proposed framework is shown in Figure 1. First, the monitored quantities from the sensor are interpolated using the PCHIP from Fritsch and Carlson (1980). The choice of using PCHIP in this paper is because the data after interpolation maintains its original values while more samples are generated for the fault prediction model. The same interpolation parameters were used in all monitored quantities. In an interval $[x(i), x(i+1)]$ with corresponding function values $f(i)$ and $f(i+1)$, and derivative values $f'(i)$ and $f'(i+1)$, the piecewise cubic Hermite interpolating polynomial $P(x)$ is given by:

$$P(x) = h00(x)f(i) + h10(x)f'(i) + h01(x)f(i+1) + h11(x)f'(i+1); \tag{1}$$

where $h00(x) = \left(1 + 2 * \frac{x - x(i)}{h(i)}\right) * \left(\frac{x - x(i+1)}{h(i)}\right)^2$;

$$h10(x) = (x - x(i)) * \left(\frac{x - x(i+1)}{h(i)}\right)^2;$$

$$h01(x) = \left(1 + 2 * \frac{x - x(i+1)}{h(i)}\right) * \left(\frac{x - x(i)}{h(i)}\right)^2;$$

$$h11(x) = (x - x(i+1)) * \left(\frac{x - x(i)}{h(i)}\right)^2;$$

and $h(i) = x(i+1) – x(i)$. x is the value at which interpolation is desired in the monitored quantity, $f(i)$ and $f(i+1)$ are the function values at the endpoints of the interval, and $f'(i)$ and $f'(i+1)$ are the derivative values at the endpoints.

Another important preprocessing function is removing the noise components from the interpolated multivariate time series data. The wavelet multivariate denoising (WMD) technique by Aminghafari, Cheze, and Poggi (2006) was used to remove the noise. WMD combines principal component analysis (PCA) and univariate wavelet denoising technique (Mallat and Hwang, 1992).

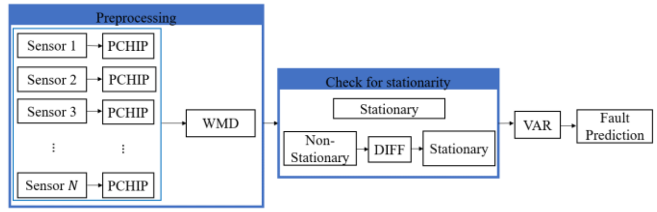

Figure 1. Block representation of the proposed framework.

Next, the stationarity of the interpolated data is verified using the Augmented Dickey-Fuller (ADF) test (Mushtaq, 2011). Based on the ADT test of each quantity, if nonstationarity is detected, the first discrete difference of the quantity for a fixed period of time is determined to obtain stationarity.

The $VAR(p)$ model represents future predictions of monitored quantities in the radar transmitter of p lagged quantities (Lütkepohl, 2005).

$$VAR(p) = A_0 + A_1Y(t-1) + A_2Y(t-2) + \cdots + A_pY(t-p) + \varepsilon(t) \tag{2}$$

where $Y(t)$ is a vector of variables at time t. A_0 is a vector of intercepts and $A_1, A_2, \ldots, A_p$ are coefficient matrices of lagged variables. $\varepsilon(t)$ is a vector of error terms assumed to be multivariate normal distribution with zero mean and covariance matrix Σ.

3. Results and Discussion

To demonstrate the performance of the proposed framework, we used the fault data from Zhai et al. (2022). The fault data contains measurements collected from 8 sensors. The monitored quantities are tagged S1, S2 to S8. S5 is constant during the time the measurements were taken. For this reason, the quantity from S5 is not considered in this paper. We used the PCHIP function in MATLAB to increase the data size. An example to generate data samples twice the size of original data is provided in Figure 2. We interpolated new values between the sample time. For instance, the interpolated value, x between the interval $x(20) = 554.7932$ kW and $x(21) = 554.0126$ kW is 554.2778 kW. To increase the data samples by 5, we interpolated 4 data values between each sample time.

The level of the WMD technique is set to 80 and the heuristic rule is selected in the WMD to keep the number of principal components associated with eigenvalues exceeding one twentieth sum of all eigenvalues. The type of wavelet filter is Daubechies (db2). The principle of Stein's unbiased risk for threshold selection rule is applied to the wavelet decomposition of the interpolated data **(**Stein, 1981**)**. One-time application of the finite discrete difference to transform all monitored quantities was adequately done to maintain stationarity. 90% of the denoised data was used in training of the prediction model and 10% as test data. The lagged of VAR is adjusted for different sample sizes.

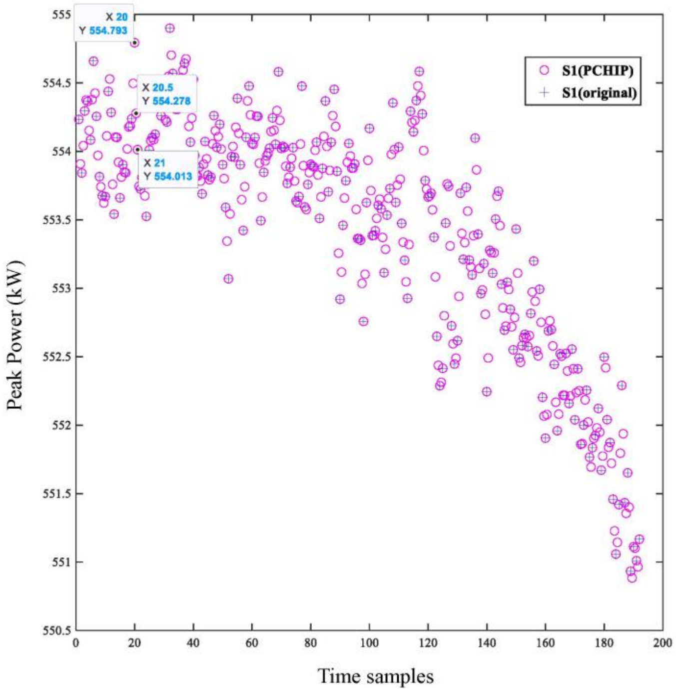

Figure 2. An example of data generated after applying PCHIP on S1 in Fault 1 from Zhai and Fang (2020).

In Table 1, the RMSE of the proposed framework without increasing the data size is compared to existing methods from Zhai et al. (2022) and Zhai and Fang (2020). This is to allow fair comparison. It is observed that the average RMSE of the proposed method for S1 in both faults is less than that of Zhai et al. (2022). However, Zhai et al. (2022) shows better prediction performance in S2.

In Table 2, the average RMSE of the proposed method with increased data sizes is compared to other existing methods. Results involved 7 sensors in the proposed method and 2 sensors in the existing methods. Despite having more number of sensors, the proposed method continues to performed better in predicting fault 1 after increasing the data size five times. The VAR exploited the interdependencies between the sensor readings and the model gets better as the data size increases. Although it is noticed that the performance of the proposed prediction method is not consistent in fault 2, which can be due to the same WMD parameter configuration settings that was used in fault 1 and fault 2.

4. CONCLUSION

This paper presented a framework for predicting the occurrence of faults in marine radar transmitter. The proposed framework relies on the vector autoregression model to exploit the interdependencies between monitored quantities. The performance of the proposed method is acceptable compared to existing methods however the proposed framework is not applicable when the monitored quantities are constant. The performance and limitation of the proposed method on interpolated fault data was also discussed. As future work, the adaptation of preprocessing operation for VAR-based fault prediction method in marine radar will be studied.

Table 1. Comparison of the proposed method and existing methods with same data size.

Methods	Sensor	RMSE	
		fault 1	fault 2
Zhai et al. (2022)	S1	0.0683	0.1300
	S2	0.0077	0.0080
Zhai and Fang (2020)	S1	0.1585	-
	S2	0.0283	-
Proposed Framework	S1	0.0896	0.0685
	S2	0.0665	0.2660
	S3	0.1270	0.0820
	S4	0.0346	0.0059
	S6	0.0364	0.0049
	S7	0.0028	0.0029
	S8	0.0017	0.0011

Table 2. Average RMSE of the proposed framework and existing methods.

Methods	Data size after PCHIP	Average RMSE	
		fault 1	fault 2
Zhai et al. (2022)	-	0.0380	0.0690
Zhai and Fang (2020)	-	0.0934	-
Proposed Framework	-	0.0512	**0.0616**
	× 2	0.0821	0.0730
	× 5	0.0501	0.2771
	× 10	0.0314	0.1317
	× 20	**0.0214**	0.1759

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